The Undetected Early European Covid-19 Outbreak

Investigating the Failures of Public Policy to Manage the Epidemic between December 2019 and April 2020

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All documentation can also be accessed on the author's homepage: www.foodandagribusiness.org

Main Messages

1. The European and Chinese epidemic branches diverged already in late November 2019. As a result, 80% of the European outbreak occurred independently of and parallel to the Chinese outbreak in Wuhan, meaning that Europe would have experienced most of the same epidemic, even if Wuhan had not happened; for America the number is 70%

2. Genetic mutation history proves without ambiguity that the virus was in Europe already in December 2019; and even earlier according to Swiss, French and Italian medical doctors

3. Excess mortality data points towards Tyrol and Bavaria being the first large epicenters in December and January

4. It appears that it was four super-spreading events, the Four Hills Ski Jumping Tournament in Austria, two professional textile trade fairs in German Munich in late January, and the Fashion Week in New York City in early February, which consecutively triggered the massive European and American outbreak of covid-19

5. The early outbreak was hidden by an exceptionally mild influenza season in Europe and was therefore initially not detected

6. When public authorities noticed the epidemic by end-February, they were unprepared and in absence of better knowledge, followed a Chinese template of public policy response

7. Those public policies of shut-downs and contact-bans, however, proved to be non-effective; voluntary social distancing responses and a natural tendency of the virus to fade away, were responsible for most of the outcome by April 2020. The public policy that would have been effective, which is ubiquitous testing and tracing, was not deployed in Europe nor the Americas.

8. The virus remains in circulation and the epidemic will therefore return in the same stealthy way by December 2020 as it did in 2019

9. Gaining a better understanding of the transmission dynamics and history is critically important to be able to manage the on-going economic, social, cultural and political effects of the epidemic. There is irrefutable evidence of both a food-borne transmission route via gastrointestinal infection, as well as textile-based smear transmission. Without better understanding of these routes it is not possible to contain the epidemic

10. Business leaders need to shape their strategies with a view towards the strong likelihood of a second or third wave of outbreaks occurring, especially considering that the public sector may be even less capable of effective responses in 2021.

Content

0. Summary

The German experience with the covid-19 epidemic is suited particularly well for investigating the effectiveness of mandatory social distancing (MSD) public policies, which were enacted for the purpose of containing the disease. The German health care system was never overloaded by cases, so that data collection on the progression of the epidemic was not distorted. Also, PCR-testing strategies were consistently applied throughout time and place, and testing capacity was always sufficient. Epidemiological data has been collected by the authorities reliably and consistently on a finely grained local basis, down to the level of 401 counties.

Germany is composed of 16 federally organized states which share similar socioeconomic conditions, but which have identifiably different traditions and lifestyles that were conducive to different transmission dynamics. These differences caused the 16 states to have sharply diverging experiences with the epidemic. This created a natural experiment to test whether the national, uniformly applied public policy bundles of MSD had proportionately uniform impact on the progression of the epidemic in the 16 states, or whether the local dynamics largely prevailed over the public policy impact.

Six identifiable bundles of social distancing were in force in Germany, each in a discrete timeframe, and can thus be compared with regards to their impact. Two of them were MSD public policy bundles of shut-downs and contact-bans respectively, two of them were natural calendar events, and two of them were voluntarily emergent responses by society to the epidemic. For the purpose of the comparison, the official German dataset of confirmed cases was enhanced to reflect the real infection rate. This enhancement was done using a German case study estimate of the real infection fatality rate, and adjustments for differences in the case demography of the states, and respective changes over time. Additional zoom-in case-study investigations support various assumptions for the utilized model.

The results of the investigation show that the two public policy bundles of MSD were not effective. Neither of them had a uniform impact across all the states, neither slowed down the progression of the epidemic nationally, and neither prevented a strong rise in the transmission rate of the epidemic at the beginning of April, nor did they influence the decline afterwards. They also did not achieve geographical eradication of the disease. By mid-May its prevalence across German regions was as widely spread as in March, and the official R number was only slightly below 1. As a public policy response for the containment of the covid-19 epidemic, both public policy bundles must be considered to be failures, as far as statistics tell (Figure 1).

The reason proposed for why the public policies were not successful (in the German context), is that the transmission dynamics of the SARS-CoV-2 virus are not yet well enough understood. Without this understanding, public policies cannot be targeted specifically enough to make a substantive difference to the progression of the epidemic. The detailed German data shed further light on the early transmission dynamics of the epidemic between December 2019 and February 2020. While much indirect evidence is mutually corroborative and elaborated in detail in Section 4 and Supplements III and IV, a smoking gun of primary evidence is yet missing.

Drawing on detailed data of mortality (partially shown in Figure 2) and genomic mutation history (partially shown in Figure 3), this proposal tells the story of how the epidemic may have been transmitted in Europe in its early days. It suggests that the ultimate origin of the European outbreak was in Innsbruck, capital city of the state of Tyrol in Austria in early December 2019. From there the virus spread throughout Austria and the Munich region in Bavaria via the Four

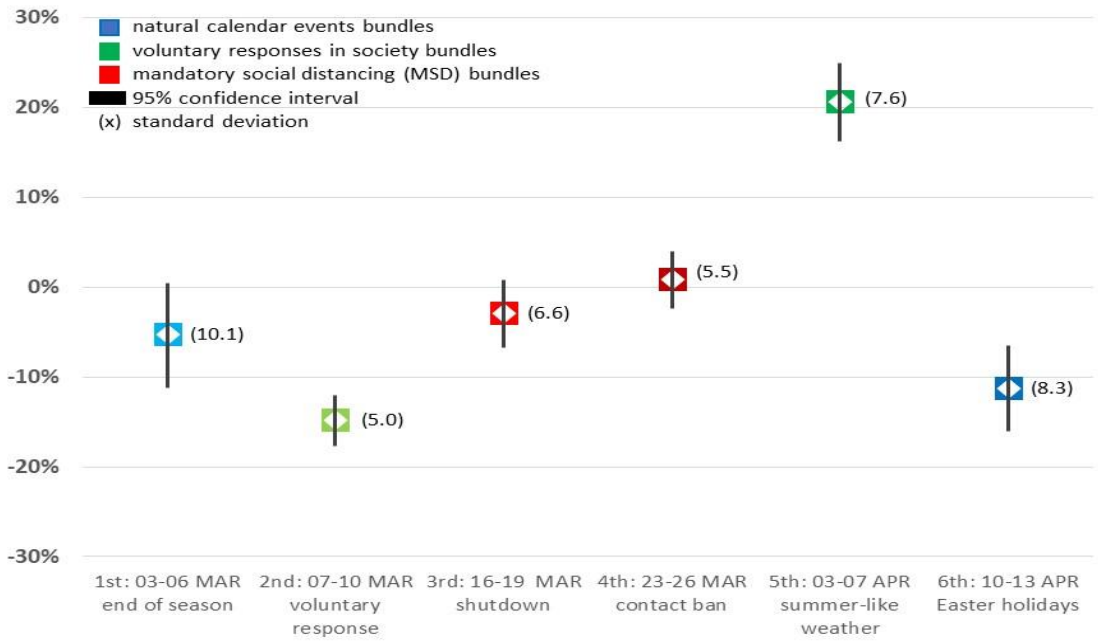
Hills Ski Jumping Tournament in early January. The virus continued to circulate latently throughout the Munich region in January, until in the beginning of February it infected the European textile industry at two professional textile trade fairs as super-spreading events. The trade fairs became the origin of the first wave of pan-European spread, especially to Northern Italy, to three Northeast regions in France and to Spain. It is also proposed that in parallel to the trade fairs in Munich, the transmission of the virus to the US East Coast occurred at another super-spreader event, this being successively the Men's and Women's Fashion Week in New York City in early February. Subsequently the virus returned via winter vacationers to the Alps, from where it launched a second, massive wave of infections in early March all across Northern Europe which ultimately triggered public policy responses, including MSD measures.

Phylogenetic data on genomic diversity and mutation history of European SARS-CoV-2 sequences from early March show with no ambiguity that the European outbreak was independent of and parallel to the January Hubei province outbreak and was several times larger than the epidemic in China. The difference was that in Europe the outbreak remained undetected until the end of February. The European source of that outbreak should be found where abnormal and irregular patterns of excess mortality and influenza activity were recorded. Such patterns can be found in Tyrol in December 2019, and then in Austria and Bavaria in January 2020. If it happened like this, then the role of textiles and potentially reinforcing feedback loops in the infection process leading to super-spreading need to be investigated. If textiles are implicated, this might have a major impact on mandatory face mask wearing.

Figure 1: Average impact on Rta of social distancing bundles among 15 German states

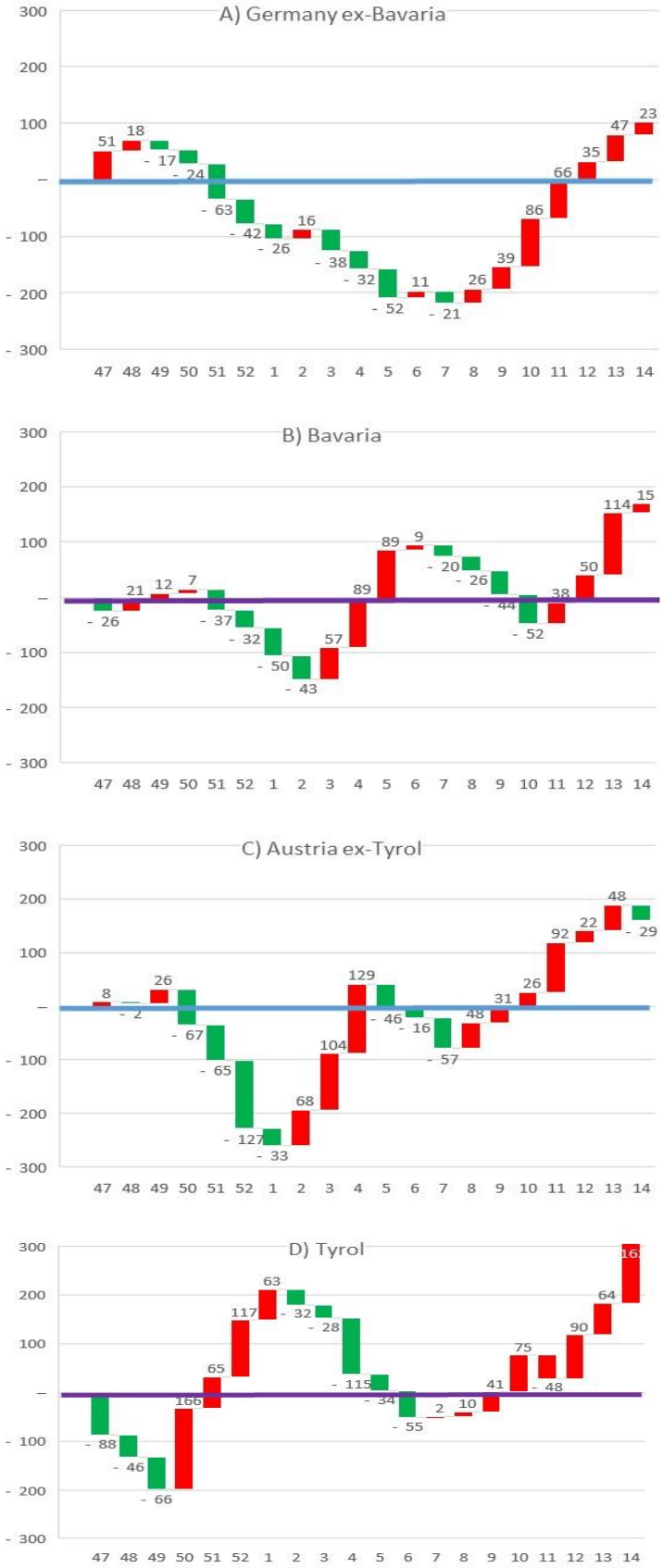
Unit of y-axis is percentage change of Rta per day in a four-day period after the bundle went into force, averaged among 15 states (Bremen is excluded as an outlier), not weighted by population size of each state. Rta is defined as the apparently transmitted reproduction number, with generation time interval of 7 days, smoothed with 3-day sliding average. Six different bundles are identified in three categories. Details in Section 3 and Supplements I, II.

>> The two MSD public policy bundles had no uniform impact across states, and did not reduce the Rta



Source: calculations for this article

Figure 2: Excess mortality in Germany, Bavaria, Austria and Tyrol, CW 47 to CW 14



Source: calculations for this article

Unit of y-axis is # of persons per 10 million population. Unit of x-axis is calendar weeks from 47 in 2019 to 14 in 2020.

The waterfall bars are the changes per week of mortality numbers versus the expected average derived from the trends of 2016, 2017 and 2019, with CW 46 as a base 0. The numbers were smoothed with a 3-unit sliding average. 2018 was excluded because it was a strong influenza year, and thus not representative. Red indicates excess mortality versus expected trend from previous years, and green indicates deficit mortality. The blue bar is the expected number from previous years. Not shown is a stochastic range.

How to read the numbers: In CW 47, Germany had a total of 18,415 deaths, 2.0% more than in CW 46. In the years 2016 and 2017 the number of deaths decreased by 1.6% from CW 46 to 47. So versus the previous years, Germany had 3.6% excess mortality, or 650 persons in CW 47. 650/83 mio population would be 78 on chart A in CW 47. Actually shown is the number 51 because of effect of 3-unit smoothing and Bavaria being excluded

Germany and Austria are shown versus their expected averages from previous years (blue bar). Bavaria and Tyrol are shown versus their respective national averages (purple bar).

>> Due to mild weather and a mild influenza season Germany experienced well below trend mortality until CW 8. From then on, Germans were increasingly killed by an unknown disease, which is proposed to be covid-19 (chart A). Officially the first two covid-19 deaths occurred in CW 11. The actual death toll might have been ~5200 by that time only in Germany, if the season had been as it was in 2016.

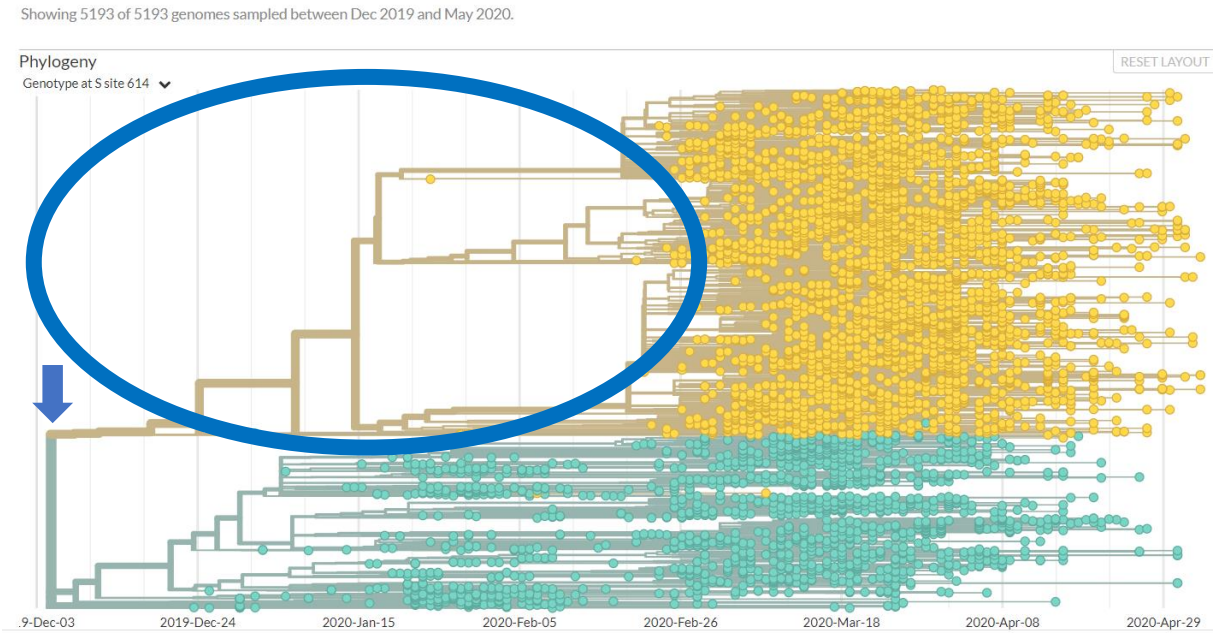
Uniquely among 15 German states (excl Bremen), Bavarians experienced a sharp rise in mortality already from CW 2 (chart B). The Bavarians shared the same irregular mortality pattern with Austria (chart C).

Uniquely among the 9 Austrian states, Tyrol experienced this irregular mortality pattern already from CW 50 in 2019 onwards. A clustering of death announcements suggests that most of this excess mortality in Tyrol was experienced in its capital city Innsbruck.

Figure 3: SARS-CoV-2 Phylogenetic Dendrogram on 14 May 2020

Unit of y-axis is the amount of known genetic diversity as indicated by the number of clade forks that could be identified in the mutation history. Unit of x-axis is the time from December 2019 to May 2020. The dates are calibrated on detection, so infection dates are up to two weeks earlier. Each dot indicates one genetic sequence being conducted. Here, 5193 dots are shown out of 24,000 known in the database on 14 May. Yellow dots refer to an early mutation which dominates the European outbreak. Green dots refer to the mutation which dominates the China outbreak. The circle refers to the undetected European outbreak with no dots, because no cases were known, and therefore not sequenced.

>> By late February 2020, the genetic diversity of the European outbreak was already much higher than in the China outbreak. This implies that there had already accumulated a much larger outbreak in Europe compared to China, which however went undetected. A large-scale outbreak must have existed because otherwise there could not have been as much genetic diversity at the beginning of March. The diversity could not have been imported from China, because all the yellow dots reside on a clade which forked off already at the end of November in a geographic location which is unknown (arrow). The assumption that this location was in China is purely driven by the first cases being detected in Wuhan in mid-December 2019, which is several weeks after this first fork with today's ancestors. All this proves that the European outbreak happened independently of and parallel to the China outbreak. The common ancestor to the European and Chinese outbreak has not yet been found. Less than 20% of the European infections have a Chinese mutation history. More details in Section 4, and Supplements III and IV.



Source: Nextstrain.org

1. Background

1.1 The challenge to public policy makers

Around the world policy makers are struggling to define public policy tools they can effectively deploy to combat the covid-19 epidemic in their countries. Several sets of public policy tools have been implemented, including hygiene rules (mandatory face mask wearing for instance), border closures, quarantine procedures, contact tracing regulations, and more. One such set of policy tools is to stipulate and enforce a wide array of different kinds of mandatory social distancing (MSD) measures in society. They include but are not limited to closures of publicly accessible facilities such as education, shopping, dining, leisure, religion or sports; the encouragement of home office and home schooling; the shutdown of non-essential production and services; restrictions on leaving living quarters; size limits on group gatherings in public or private spaces; keeping physical distances to non-household members in public; and more. While, as of the date of writing this article, policy makers around the world are loosening MSD measures, they are not being entirely dissolved, and there remains the Sword of Damocles of their reintroduction hanging over societies.

As a public policy, such measures of MSD are particularly controversial due to the large amount of social, cultural, political and economic disruption they cause in society. They are implemented on three main assumptions:

1) a high proportion of infected persons are non-symptomatic but infectious [1];
2) the SARS-CoV-2 virus is transmitted predominantly via airborne infection [2];
3) covid-19 is highly infectious and therefore highly transmittable [3], and therefore requires rigorous social distancing of people from each other in order to prevent infections.

1.2 The challenge of faulty assumptions

These three assumptions rest on numerous anecdotal reports and investigations about whether and how the virus spreads in close-proximity community situations. Evidence comes from cruise ships and aircraft carriers, various well documented super-spreader events, and numerous case tracing reports on confirmed transmissions in private and public gatherings such as restaurants, parties, seminars, choir rehearsals, conferences, dormitories and more. These three assumptions also appear to be confirmed in hindsight by introduction of MSD measures for instance across Europe in mid-March that are popularly credited by scientists, journalists and politicians for the success in abating a first wave of the epidemic.

The first assumption is true with certainty. The second assumption may yet turn out to be false, as fecal-to-oral, waterborne or foodborne transmission are viable too [4]. The third assumption is certainly not true. Extensive case tracing work in Taiwan [5], and confirmed in many places elsewhere, has shown that it usually takes several thousand close encounters for an infection to occur. This in contrast to measles for instance, where 9 out of 10 non-immune persons with close contact will develop measles [6]. Generally, compared to other infectious diseases, covid-19 has an extremely low degree of infectivity. The problem arises because, in a few rare cases, there will be a super-spreading person engaging in a super-spreading activity, who then infects hundreds or in some cases thousands of other persons [7]. How and why that happens is a big mystery, and it is possibly the single most important question about the covid-10 epidemic. More on this subject will be covered in Section 5 of this article.

1.3 The lack of data-driven evidence

If the nature of the transmission paths of covid-19 is still a big mystery, then it should not be a surprise if public policies designed to combat the epidemic fail to be effective. This is certainly true for MSD measures, as this article proves, and it may yet prove true for other public policies such as mandatory face mask wearing. Apart from the intuitive appeal that MSD measures and face mask wearing will slow down or even stop the spread of covid-19 in communities, there is little data-driven evidence of how effective they are as a public policy tool.

While a growing number of epidemiological models have attempted to estimate the effectiveness of MSD public policies and have published their results accordingly, they are often based on assumptions which tend to be tautological: first the various complicated parameters of the models are tuned to follow the observed progression dynamics of the epidemic, and afterwards the observed progression is published as a confirmation of the parameters. Two examples of this false methodology are studies on MSD in Germany by the *Max-Planck-Gesellschaft* [8], and France published in *Science* [9]. Some researchers tried to overcome this tautology by conducting an international comparison. For instance, an often-cited estimate on the effectiveness of MSD was published by the *Imperial College London* (ICL) in its Report 13 on 30 March [10]. A team around Feuerriegel et al. at *ETH Zurich* published a similar and controversial effort on 28 April [11]. An American attempt for Seattle was published in *Emerging Infections Diseases* [12]. However, these approaches also suffer from severe methodological problems. There are too many confounding factors that are not readily observable in international comparisons: differing policies, national cultures, stages of disease progression, socioeconomic conditions, testing strategies, rates of social compliance to the measures, personal interaction patterns, citizen-government relationship and more, are liable to document spurious correlations instead of causality.

For instance, was the unequivocal success in containing the epidemic in New Zealand due to an extremely strict public policy on MSD measures? Or was it due to the timeliness of their introduction? Or was it due to the high degree of social trust and coherence that prevails in New Zealand society? If it was the first two factors, the policy should have worked even better in South Africa, where the government acted even more draconian and even earlier than New Zealand – but with little success to show for. If it was social trust, then why does Sweden still have so many infections? If it is a combination of social trust and tough measures, then why have Poland and Singapore been struggling so much? Why did Geneva in Switzerland become one of the most infected cities in Europe, ahead of even Bergamo, if the Swiss MSD were supposedly so effective? Real proof of effectiveness of MSD public policies require non-confounded control groups in natural experiments (assuming that a real experiment is ethically not feasible), so that the effects of the public policy can be validly isolated in the sample.

The German experience provides an example on the danger of spurious correlations. Figure 4 shows maps of the infection levels per county in Germany, Switzerland and the Netherlands. Adjacent to them are maps of share of catholic believers in those counties. The correlation is high in all three countries. However, it is obvious that believing in the catholic faith has no biological relationship with being susceptible to covid-19. Furthermore, there appears to be a clear correlation between living in the South of a country and being infected, for which there is also clearly no biological cause. Correlations are the curse of modern social sciences.

The problem is with the unobserved confounded factors that are the real underlying cause. There is only one valid way to expose causality, which is to examine a natural experiment, as

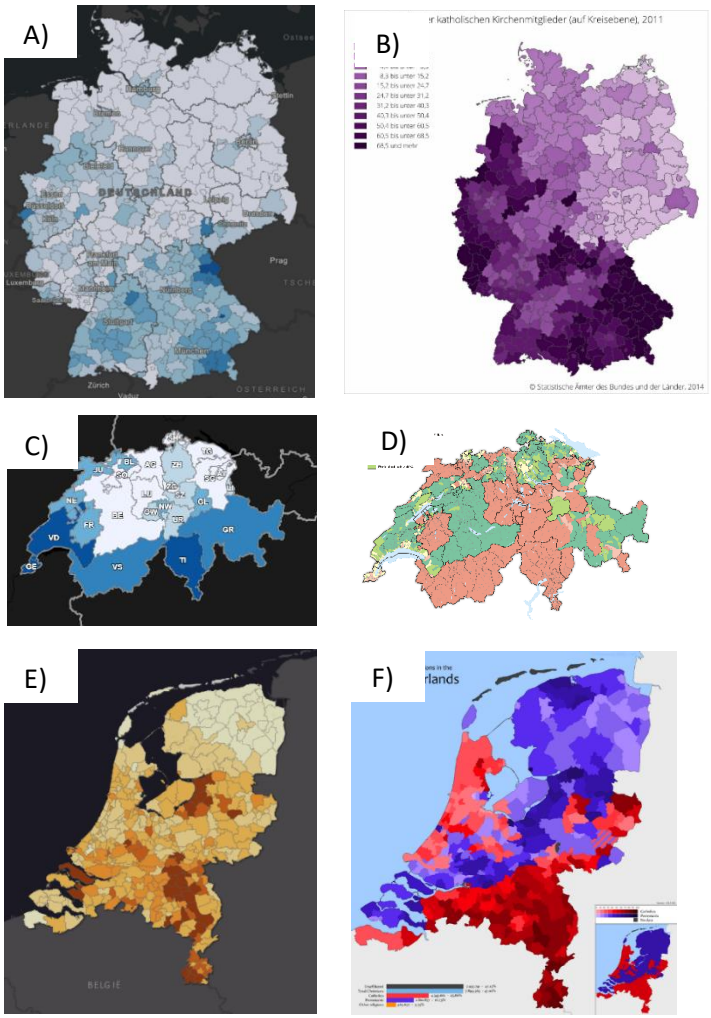
Thad Dunning explained in his seminal book on the subject [13]. (A possible underlying cause for why SARS-CoV-2 seems to be attacking Catholics in these three countries, may be the frequency of singing in churches, which has been proven to be a highly infectious activity.)

1.4 The answer which the natural experiment in Germany can provide

Germany is a federal country with 16 states, where almost identical public policies on MSD measures were implemented at the same time, but where the covid-19 epidemic took sharply diverging courses in the states. This created a natural experiment for investigation which Dunning would approve of. The analysis in this article explores the rich German dataset for an assessment of the effectiveness of six different bundles of social distancing on reducing the covid-19 epidemic spread. Two bundles were triggered by natural calendar events, two bundles were triggered by voluntarily emergent responses in society, and two bundles were public policies of MSD.

Subsequently, the analysis proposes a hypothesis on the early transmission history in Europe that can also be observed from the data, but not finally proven, because critical direct evidence is missing. The hypothesis aims to broaden the arena of analysis on the nature of the transmission dynamics, with which the SARS-CoV-2 virus is attacking global humanity.

Figure 4: Covid-19 infection levels and Catholicism in three countries



A) infection level German counties, dark blue = more infected

B) share of Catholics German counties, dark purple = more catholic

C) infection level Swiss cantons, dark blue = more infected

D) share of Catholics Swiss cantons, red = more catholic

E) infection level Dutch municipalities, dark brown = more infected

F) share of catholics Dutch municipalities, red = more catholic

Sources:

A, C, E: https://npgeo-corona-npgeo-de.hub.arcgis.com/

B: https://fowid.de/meldung/deutschland-3-katholische-sueden-und-westen

D: Wikipedia commons: Karte Religionen der Schweiz 2017.01.01.png

F: Christian denominations in the Netherlands, 2014

2. Methodology

2.1 Germany as a case study and its available data on confirmed cases

The German regional experience with SARS-CoV-2 should be particularly well suited to assess the effectiveness of public policy mandatory social distancing (MSD) measures, as most of the confounding factors can be eliminated from the analysis. The details are explained in Supplement I a, b and c). They are mostly related to Germany being a heavily infected country, where a consistent covid-19 PCR-testing scheme was nationally applied, with transparent and detailed data provision on the level of 16 states and 401 counties, and no distorting factors such as an overloaded health care system or shortage of testing.

Germany is a federally organized country with 16 states (*Länder*). There are identifiable regional differences in traditions and lifestyles, which seem to have led to significant differences in the progression of the epidemic per state. In order to confirm that it was not the variance in socioeconomic conditions which influenced the transmission dynamics, but those traditions and lifestyles, various control factors were analyzed on the level of 401 counties. The details are explained in Supplement I e). In brief, no significant correlations could be identified between the infection levels in counties and any of three key socioeconomic variables: a) urban versus rural living conditions as measured by an index of the German government; b) household income as measured by taxable income; c) population density of a county – neither in a single, nor in a multivariate analysis for the three jointly. Also, dilapidation or old age of housing stock could be excluded as an influential factor in a separate analysis.

In terms of traditions and lifestyles, there are strong correlations between covid-19 infection levels and differences in household composition by county. Counties with proportionately more households consisting of couples with children are positively correlated to higher infection rates, whereas counties with more couples without children are negatively correlated. Having more single person households is also negatively correlated. Single parents or shared-living households have no significant correlation. When focusing only on families, married couples are positively correlated and unmarried couples are negatively correlated. When focusing on the size of the family, then four or five persons in the family are highly correlated, while two or three persons in the family are negatively correlated. Finally, having a senior citizen in the household is mildly positively correlated. These traditions and lifestyle choices, either directly or indirectly via confounding unobserved factors, indicate differences in infection levels prevailing per county.

Besides singing in churches, other lifestyle choices that made a difference to the infection levels, as will be explained further on, are the inclination for Alpine winter vacationing, an inclination for carnival or other festivals, and involvement in the fashion industry. All of these differ strongly by regions in Germany.

2.2 The public policy bundles of mandatory social distancing and the natural experiment

The German public policy bundles of mandatory social distancing (MSD) measures were coordinated at the national level and implemented at the same time and at nearly the same level of severity across all 16 states. This provides a natural experiment of 16 different contexts and diverging epidemic experiences, on which the same bundles of measures were enacted, and where the outcomes of the epidemic were monitored with the same testing strategies. This

natural experiment allows for a control check: The same public policies with the same testing and reporting strategies and the same health care system, should yield the same or at least a similar level of proportional impact in all states, if they are to be uniformly effective. If they resulted in substantially different or even no impacts, then the local progression dynamics of the epidemic per state dominated the imposed national public policy, and by implication, this public policy tool was either not or only marginally effective.

A deeper investigation to understand the state and regional progression of the epidemic picks out case studies from the 401 counties (*Städte und Landkreise*) for which data is also available at the same level of detail as for state or national level. These case studies are shown in detail in Supplement V.

2.3 Calculation method of the daily case numbers

The analysis assumes that the confirmed case data do not represent the real number of infected cases. This would not matter as long as the relationship between confirmed cases and the real numbers is always the same. However, both plausibility and evidence suggest that the relationship has changed over time, because the case discovery rate changed over time. In the beginning of the epidemic the discovery rate was low as would be expected. As patients began to receive tests, the discovery rate went up. Later on, in the course of April, the discovery rate went down again as evidenced by mortality data from late April and early May.

A better indicator of infection activity is the incidence of death. On the assumption that the general infection fatality rate (IFR) has remained the same throughout the analysis period, the deaths which are recorded indicate the actual number of infections that occurred some weeks earlier. While patients may have intentionally or non-intentionally avoided being tested, they could not have avoided death. This assumption is justified for Germany, because at no time did the health care system experience a collapse or even was particularly stressed, so that there were no respective distortion effects. Neither were there improvements of medical treatment throughout the analysis period which would have changed the IFR.

However, the IFR does differ by demographic groups, both by age and by gender. The analysis therefore took a general IFR which was determined for the German case study of the Gangelt outbreak in Heinsberg county for the beginning of April to be 0.41% among a reasonably representative sample of almost 1000 persons out of a 12,500 strong community [14]. This general IFR was adjusted accordingly to the case demography of the states and the case demography over time to yield state-specific and week-specific IFRs. This calculation provided a daily death-incidence and age-adjusted factor (DAF) which, applied to the reported daily new confirmed case numbers produces the daily new real case (NRC) numbers. The Gangelt IFR is confirmed by the U.S. CDC which as per 29 April uses 0.4% as the current best estimate [15].

The remainder is arithmetic. Each daily count of new confirmed cases (NCC) per state was divided by its applicable time- and state-specific IFR to yield the actual NRC per day. For purposes of smoothing the daily data, a 3-day sliding average was applied. The calculations suggest that Germany-wide, only 8.8% of all covid-19 cases were detected by the PCR testing campaign. No mass-serological tests have been conducted in Germany yet. But this scale of a 90% undetected case load is confirmed by mass-serological tests in Geneva [16], which had similar testing strategies as Germany. More details of the calculation are provided in Supplement II a) and b) and the data tables are provided in Excel format in Supplement VI.

2.4 The apparently transmitted reproduction number Rta, and intervals

This analysis does not estimate the basic reproduction number R0 for covid-19, nor even the general effectively transmitted reproduction number Rt (also called Re). Instead, the analysis uses the concept of Rta, which is defined as the apparently transmitted reproduction number in a local context, in this case the context of each of the 16 states in Germany. This choice is informed by the assumption that for covid-19 the R0 and Rt are relatively meaningless concepts for the purpose of framing public policy (regardless of its popularity in German public discourse where an official R is published each day). The subject will be dealt with in more depth in Section 5, and is also informed by the case studies in Supplement V. A dashboard monitoring of the Hong Kong covid-10 epidemic publishes such an Rta in a similar manner [17]. Kevin Systrom is providing similar real time estimations for the United States [18].

All R numbers in this analysis therefore refer to the Rta concept. Throughout the analysis, it is assumed that the generation time interval is seven days, meaning the length of one infection cycle from one infected person to the next, or from infector to infectee, is on average 7 days. The Rta together with the generation time interval results in the apparent transmission rate per state. Vice versa, given a generation time interval of seven days, the apparent Rta can be easily calculated from the numbers of new real cases, by dividing the current cohort with the cohort of seven days ago. Effectiveness of the social distancing bundles are measured in terms of impact on Rta, meaning how many new infectees were apparently generated by the previous generation, regardless of how they were generated.

The Rta in this analysis are deliberately not calculated by incorporating advanced statistical probability distributions, for instance Bayesian methods, Poisson distributions or with negative binomials. This would require knowledge about the parameters of these distributions, which currently does not exist. A normal distribution might be as wrong as distributions derived from the confirmed case numbers, which might be as wrong as using simply no distribution. Using such advanced statistical methods makes the model look more sophisticated, but may produce more statistical artefacts than reality. Instead, the analysis in this paper calculates the Rta mechanically by dividing the 3-day sliding average number of apparent new real cases by another 3-day sliding average from seven days earlier.

The generation time interval assumed for one infection to the next is seven days. The infection to registration interval is assumed to be 14 days in March, gradually reducing down to 10 days during the first three weeks of April. The infection to registration of death interval is assumed to be 28 days throughout the study period. All these numbers fit best to the German data and are well supported by the literature. More detail on the intervals is given in Supplement I d).

2.5 Excess mortality and genetic mutation history for the early transmission history

Section 4 analyses excess mortality data for German and Austrian states in order to chart the course of the progression of the early epidemic until February 2020. More details on the excess mortality methodology are provided in Supplement II c).

Section 4 also analyzes genetic mutation history and matches it with the progression dynamics of the German and Austrian epidemic. The corresponding methodologies are explained in Section 3 and Supplements III and IV.

3. Results of Assessment of Effectiveness of MSD Public Policy

3.1 General findings

Figure 5 displays the apparently transmitted reproduction number (Rta) per state as calculated for each day of the two months March and April 2020. Figure 6 shows for the same dates and the same 16 states, the percentage changes in the Rta of figure 5. Thus Figure 5 shows the conditions of absolute Rta levels per day, while Figure 6 shows the trend per day.

The rightmost column for the German average shows that the Rta had been around 3 at the beginning of March, and rapidly came down towards 1 by 09 March. It then decreased further to as low as 0.6 at the end of March, before increasing again towards 1.5 during the beginning of April. This general picture has more pronounced and somewhat earlier swings of the Rta compared to the official R reports published by the German federal agency Robert Koch Institute (RKI), but there is overall similarity. This general average German picture has been falsely used by German government, various research institutes, and public media to proclaim that the public policies of MSD were successful in reducing the spread of the epidemic [19].

However, when the general German average is split into 16 different states, it reveals widely diverging progression dynamics. Those dynamics are best understood with Figure 6 where the trends of Rta are shown.

It is noteworthy that out of 16 states, only four have a higher rate of infection than the German average, including Saarland which is the second smallest state in Germany, and Hamburg which is the fourth smallest state. This means that the German average is heavily dominated by the two large southern states of Bavaria and Baden-Wuerttemberg, which have had high rates of infection.

Details on data compilation and calculation methods are provided in Supplement I and II.

3.2 The six bundles of social distancing which could be identified and effects measured

No	Date	Content	Category
1	03-06 March	Winter vacation and Carnival season end	Natural calendar event
2	07-10 March	Voluntary social distancing behavior	Emergent response
3	16-19 March	Shut-downs of public life	Mandatory public policy
4	23-26 March	Contact-bans in private life	Mandatory public policy
5	03-07 April	First summer-like weekend	Emergent response
6	10-13 April	Easter Holidays	Natural calendar event

The following will provide a brief overview of how effective each bundle was in influencing the Rta. The summary in terms of average impact per day and standard distribution around that average is shown in Figure 1. More details on the sociopolitical context of each bundle and contents of each bundle are provided in Supplement I f).

Figure 5: Apparently transmitted R (Rta) by German state per daily cohort

Right date column refers to the date of official local registration of the case, and left date column refers to the imputed corresponding day of infection. In March the day of infection is imputed to be 14 days before the day of registration. In the course of April, the infection to registration interval is imputed to gradually shorten to ten days. The average generation time interval is assumed to be 7 days throughout both months, which fits best to the data and the literature. Division of the new real case numbers with those of seven days previously, using a 3-day sliding average for smoothing, produces the Rta number. The Rta of 2 in February is a lumpsum assumption due to a lack of data. Each column is one German state, plus the German total at the far right (ALL). The coloration is deeper blue towards lower Rta below 1, and deeper red towards higher Rta above 1. The states are sorted from left to right in the sequence of their cumulative number of confirmed cases per population as per 22 April, with Bavaria showing as the highest with 303 infected per 100,000 population.

		infections per 100k		303	271	245	236	172	148	140	122	118	108	101	101	92	87	66	41	181
		infection	reported	BAY	BA-WÜ	SAAR	HAM	NRW	BER	RP	HESS	NIE-SA	SACH	BB	BREM	THÜR	S-HOL	S-ANH	M-POM	ALL
14 Days Reporting Interval	Mon	17. Feb.	2. Mrz.	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00
	Tue	18. Feb.	3. Mrz.	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00
	Wed	19. Feb.	4. Mrz.	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00
	Thu	20. Feb.	5. Mrz.	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00
	Fri	21. Feb.	6. Mrz.	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00
	Sat	22. Feb.	7. Mrz.	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00
	Sun	23. Feb.	8. Mrz.	2,00	2,50	2,00	2,00	2,66	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,18
	Mon	24. Feb.	9. Mrz.	2,00	3,59	2,00	2,00	3,74	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,45
	Tue	25. Feb.	10. Mrz.	2,00	3,60	2,00	2,00	2,69	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,35
	Wed	26. Feb.	11. Mrz.	2,58	3,86	2,00	2,00	2,45	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,44
	Thu	27. Feb.	12. Mrz.	3,00	3,80	2,00	2,00	2,62	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,54
	Fri	28. Feb.	13. Mrz.	4,64	4,81	2,00	2,00	3,12	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,94
	Sat	29. Feb.	14. Mrz.	4,44	5,18	2,00	3,12	3,97	1,66	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	3,20
	Sun	1. Mrz.	15. Mrz.	3,43	5,80	2,00	3,04	3,90	1,56	2,00	2,68	3,03	2,00	2,00	0,58	2,00	2,00	2,00	2,00	3,24
	Mon	2. Mrz.	16. Mrz.	2,78	4,16	2,00	3,64	3,82	1,64	2,72	4,43	3,36	2,28	2,87	0,58	2,09	2,62	2,00	2,00	3,21
	Tue	3. Mrz.	17. Mrz.	2,92	3,48	2,10	2,71	2,91	1,88	3,18	4,34	3,36	3,07	3,60	0,48	3,42	2,21	1,75	2,40	2,97
	Wed	4. Mrz.	18. Mrz.	3,34	2,69	1,85	2,78	2,50	2,02	2,48	3,91	2,56	3,22	2,52	1,27	3,49	2,14	1,67	2,39	2,69
	Thu	5. Mrz.	19. Mrz.	3,09	2,26	1,70	2,66	1,91	2,02	1,90	2,76	2,12	3,20	1,97	1,63	4,68	1,84	1,89	2,24	2,29
	Fri	6. Mrz.	20. Mrz.	2,86	1,62	1,56	1,94	1,72	2,16	1,52	1,89	1,83	2,61	1,46	2,85	2,76	1,74	2,39	1,99	1,95
	Sat	7. Mrz.	21. Mrz.	2,39	1,44	1,48	1,25	1,21	1,92	1,19	1,40	1,38	1,80	1,10	1,99	3,22	1,35	4,19	1,58	1,55
	Sun	8. Mrz.	22. Mrz.	2,01	1,06	1,48	0,95	0,95	1,68	0,91	1,12	1,09	1,45	0,81	2,72	1,90	1,27	1,55	0,90	1,21
	Mon	9. Mrz.	23. Mrz.	1,57	1,13	1,26	0,90	0,69	1,33	0,79	1,02	0,96	1,14	0,62	1,21	1,87	1,30	1,32	0,65	1,02
	Tue	10. Mrz.	24. Mrz.	1,43	0,97	0,98	0,78	0,72	1,18	0,76	0,85	0,91	1,07	0,79	1,08	1,40	1,27	1,02	0,50	0,96
	Wed	11. Mrz.	25. Mrz.	1,40	1,07	0,94	0,62	0,65	1,08	0,80	0,81	0,94	0,87	0,76	0,61	1,15	1,09	0,95	0,48	0,94
	Thu	12. Mrz.	26. Mrz.	1,32	0,99	0,99	0,57	0,73	0,94	0,87	0,82	1,01	0,81	0,87	0,53	0,87	0,97	0,87	0,56	0,95
	Fri	13. Mrz.	27. Mrz.	1,17	1,09	1,15	0,60	0,68	0,92	0,98	0,92	1,16	0,81	0,85	0,55	0,82	1,01	0,98	0,84	0,95
	Sat	14. Mrz.	28. Mrz.	0,99	0,91	1,03	0,60	0,77	0,81	0,81	0,94	1,23	0,85	0,83	0,58	0,70	0,92	1,03	1,66	0,90
13 Days	Mon	16. Mrz.	29. Mrz.	0,88	0,91	0,91	0,52	0,68	0,80	0,62	0,71	1,00	0,82	1,06	0,58	0,67	0,75	0,89	1,19	0,81
	Tue	17. Mrz.	30. Mrz.	0,92	0,72	1,20	0,44	0,72	0,69	0,55	0,65	0,80	0,75	1,21	0,46	0,55	0,62	0,65	0,93	0,75
	Wed	18. Mrz.	31. Mrz.	0,95	0,77	1,62	0,54	0,76	0,64	0,72	0,71	0,76	0,76	0,99	0,67	0,58	0,71	0,61	0,78	0,80
	Thu	19. Mrz.	1. Apr.	0,83	0,69	1,79	0,60	0,76	0,55	0,70	0,71	0,64	0,74	0,86	0,46	0,62	0,72	0,51	0,76	0,74
	Fri	20. Mrz.	2. Apr.	0,80	0,73	1,39	0,70	0,73	0,60	0,70	0,69	0,64	0,83	0,82	0,65	0,63	0,75	0,47	0,64	0,74
	Sat	21. Mrz.	3. Apr.	0,75	0,69	1,30	0,68	0,69	0,58	0,57	0,63	0,58	0,81	0,94	0,53	0,65	0,66	0,48	0,60	0,70
12 Days	Mon	23. Mrz.	4. Apr.	0,80	0,71	1,17	0,74	0,72	0,71	0,63	0,70	0,65	0,87	1,03	0,89	0,78	0,70	0,66	0,52	0,74
	Tue	24. Mrz.	5. Apr.	0,78	0,58	1,18	0,77	0,76	0,58	0,68	0,72	0,57	0,62	0,67	0,54	0,76	0,64	0,63	0,38	0,70
	Wed	25. Mrz.	6. Apr.	0,75	0,58	0,75	0,99	0,76	0,74	0,72	0,69	0,74	0,62	0,68	1,44	0,88	0,72	0,65	0,48	0,71
	Thu	26. Mrz.	7. Apr.	0,73	0,59	0,80	0,94	0,78	0,76	0,67	0,75	0,76	0,63	0,85	0,93	0,81	0,70	0,62	0,46	0,71
	Fri	27. Mrz.	8. Apr.	0,63	0,60	0,70	0,77	0,71	0,72	0,65	0,81	0,80	0,58	0,91	1,08	0,78	0,71	0,81	0,48	0,67
	Sat	28. Mrz.	9. Apr.	0,55	0,56	0,87	0,63	0,66	0,56	0,60	0,74	0,71	0,53	0,86	0,44	0,64	0,55	0,78	0,35	0,61
11 Days	Mon	30. Mrz.	10. Apr.	0,49	0,60	0,56	0,62	0,65	0,50	0,59	0,70	0,66	0,46	0,75	0,57	0,51	0,50	0,66	0,47	0,57
	Tue	31. Mrz.	11. Apr.	0,48	0,63	0,44	0,56	0,64	0,47	0,54	0,65	0,65	0,59	0,78	0,46	0,47	0,39	0,52	0,51	0,56
	Wed	1. Apr.	12. Apr.	0,56	0,80	0,27	0,56	0,65	0,68	0,64	0,76	0,62	0,72	0,74	1,08	0,72	1,27	0,54	1,00	0,65
	Thu	2. Apr.	13. Apr.	0,66	0,68	0,43	0,47	0,68	0,59	0,77	0,92	0,66	0,84	0,64	0,56	0,89	1,00	0,58	0,31	0,68
	Fri	3. Apr.	14. Apr.	0,74	0,78	0,51	0,65	0,76	0,70	0,88	0,96	0,72	0,65	0,64	0,91	0,93	0,94	0,71	0,55	0,76
	Sat	4. Apr.	15. Apr.	0,93	0,95	0,58	0,76	1,05	0,83	1,05	1,14	1,00	0,93	0,86	1,97	1,33	0,65	0,88	0,63	0,96
10 Days	Mon	6. Apr.	16. Apr.	1,10	1,14	0,57	1,16	1,24	1,24	1,25	1,35	1,17	0,83	1,25	3,77	1,65	0,99	1,56	1,13	1,16
	Tue	7. Apr.	17. Apr.	1,33	1,22	0,83	1,18	1,56	1,63	1,66	1,65	1,51	1,13	1,68	3,43	2,57	1,29	2,14	0,89	1,41
	Wed	8. Apr.	18. Apr.	1,46	1,27	0,75	1,16	1,71	1,92	1,60	1,79	1,49	0,73	1,96	2,88	2,23	1,40	2,66	0,65	1,49
	Thu	9. Apr.	19. Apr.	1,38	1,23	1,02	0,87	2,00	1,40	1,17	1,59	1,95	0,96	2,53	2,81	2,28	0,59	1,80	0,70	1,48
	Fri	10. Apr.	20. Apr.	1,14	1,36	0,91	1,00	1,64	1,15	0,70	1,35	1,48	0,81	2,14	2,76	1,86	0,70	1,65	0,54	1,30
	Sat	11. Apr.	21. Apr.	0,80	1,01	0,98	0,86	1,13	0,92	0,69	1,01	1,07	0,87	1,52	3,72	1,76	0,69	1,50	0,49	0,98
	Sun	12. Apr.	22. Apr.	0,74	0,88	0,83	0,89	0,74	0,96	0,66	0,86	0,78	0,62	0,97	1,53	1,28	1,10	1,45	0,27	0,81
	Mon	13. Apr.	23. Apr.	0,69	0,75	0,68	0,64	0,62	0,78	0,59	0,68	0,65	0,65	0,81	1,46	1,12	0,94	0,86	0,41	0,70
	Tue	14. Apr.	24. Apr.	0,70	0,60	0,54	0,77	0,54	0,76	0,46	0,64	0,57	0,53	0,74	0,64	0,88	0,89	0,71	0,70	0,63
	Wed	15. Apr.	25. Apr.	0,62	0,50	1,00	0,77	0,51	0,65	0,55	0,56	0,55	0,79	0,66	1,24	0,97	0,87	0,50	1,33	0,58
	Thu	16. Apr.	26. Apr.	0,67	0,46	0,93	1,08	0,46	0,81	0,74	0,64	0,53	0,65	0,49	1,09	0,78	0,60	0,61	1,28	0,58
	Fri	17. Apr.	27. Apr.	0,63	0,51	0,83	0,59	0,46	0,95	0,88	0,67	0,56	0,71	0,60	1,61	0,96	0,56	0,40	3,67	0,59
	Sat	18. Apr.	28. Apr.	0,65	0,48	0,54	0,60	0,49	0,99	0,75	0,79	0,58	0,69	0,71	0,90	0,86	0,55	0,45	2,47	0,61
	Sun	19. Apr.	29. Apr.	0,51	0,44	0,75	0,50	0,63	0,76	0,66	0,74	0,55	0,74	0,72	0,96	0,83	0,49	0,41	3,48	0,58
	Mon	20. Apr.	30. Apr.	0,45	0,52	0,83	0,48	0,69	0,59	0,71	0,74	0,48	0,72	0,51	0,72	0,65	0,43	0,43	1,26	0,56
	Tue	21. Apr.	1. Mai.	0,39	0,64	0,77	0,25	0,69	0,43	0,61	0,61	0,41	0,67	0,42	0,72	0,58	0,39	0,34	0,69	0,53
	Wed	22. Apr.	2. Mai.	0,40	0,79	0,37	0,19	0,65	0,57	0,40	0,64	0,35	0,57	0,40	0,70	0,34	1,27	0,41	0,43	0,55
	Thu	23. Apr.	3. Mai.	0,40	0,65	0,39	0,21	0,61	0,76	0,35	0,46	0,57	0,50	0,42	0,89	0,51	1,91	0,30	0,48	0,53

Figure 6: Trend of changes in Rta by German state per daily cohort

For the same dates and the same 16 states as in Figure 5, Figure 6 displays a 3-day sliding average of percentage changes in the Rta. The coloration is deeper blue for a trend of declining Rta values indicated by negative percentages, and deeper red for a trend of increasing Rta values. The six bundles are indicated by green letters from 1st to 6th for each of the four days when they went into force. For the states from Berlin leftwards towards Mecklenburg-Vorpommern, the initial increases of Rta at the end of February are likely to be statistical artefacts due to the lumpsum assumption of an Rta of 2 throughout February and early March. This assumption was necessary because confirmed case infections were absent or rare in most of these states until and including the first week of March. The state of Bremen is an obvious outlier in both figures and will not be considered much in the further analysis. Bremen is the smallest state in Germany, with 0.8% of the German population.

		infections per 100k		303	271	245	236	172	148	140	122	118	108	101	101	92	87	66	41	181
		infection	reported	BAY	BA-WÜ	SAAR	HAM	NRW	BER	RP	HESS	NIE-SA	SACH	BB	BREM	THÜR	S-HOL	S-ANH	M-POM	ALL
14 Days Reporting Interval	Mon	17. Feb.	2. Mrz.																	
	Tue	18. Feb.	3. Mrz.	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Wed	19. Feb.	4. Mrz.	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Thu	20. Feb.	5. Mrz.	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Fri	21. Feb.	6. Mrz.	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Sat	22. Feb.	7. Mrz.	0%	8%	0%	0%	11%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	3%
	Sun	23. Feb.	8. Mrz.	0%	23%	0%	0%	25%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	7%
	Mon	24. Feb.	9. Mrz.	0%	23%	0%	0%	15%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	6%
	Tue	25. Feb.	10. Mrz.	10%	17%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	4%
	Wed	26. Feb.	11. Mrz.	15%	2%	0%	0%	-10%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
	Thu	27. Feb.	12. Mrz.	33%	11%	0%	0%	6%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	8%
	Fri	28. Feb.	13. Mrz.	22%	11%	0%	19%	18%	-6%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	10%
	Sat	29. Feb.	14. Mrz.	9%	15%	0%	18%	15%	-8%	0%	11%	17%	0%	0%	-24%	0%	0%	0%	0%	9%
	Sun	1. Mrz.	15. Mrz.	-15%	-3%	0%	24%	8%	-6%	12%	33%	21%	5%	14%	-24%	2%	10%	0%	0%	3%
	Mon	2. Mrz.	16. Mrz.	-12%	-11%	2%	-3%	-9%	5%	18%	32%	21%	16%	23%	-29%	23%	5%	-4%	7%	-2%
	Tue	3. Mrz.	17. Mrz.	0%	-22%	-2%	-1%	-13%	9%	10%	18%	-4%	18%	13%	49%	23%	4%	-6%	7%	-6%
	Wed	1st 4. Mrz.	18. Mrz.	4%	-18%	-5%	-9%	-21%	8%	-9%	-14%	-14%	13%	-9%	58%	33%	-11%	-1%	5%	-11%
	Thu	5. Mrz.	19. Mrz.	0%	-22%	-9%	-10%	-16%	5%	-22%	-24%	-18%	-5%	-26%	89%	-2%	-8%	12%	-6%	-13%
	Fri	6. Mrz.	20. Mrz.	-10%	-19%	-7%	-22%	-21%	-1%	-22%	-29%	-19%	-17%	-24%	24%	3%	-14%	38%	-13%	-17%
	Sat	7. Mrz.	21. Mrz.	-13%	-22%	-4%	-29%	-20%	-6%	-22%	-26%	-20%	-23%	-26%	27%	-22%	-11%	13%	-25%	-19%
	Sun	2nd 8. Mrz.	22. Mrz.	-18%	-10%	-7%	-22%	-26%	-15%	-19%	-18%	-19%	-24%	-25%	-16%	-9%	-9%	-1%	-30%	-19%
	Mon	9. Mrz.	23. Mrz.	-16%	-11%	-13%	-14%	-15%	-15%	-13%	-15%	-13%	-16%	-7%	-10%	-22%	-2%	-33%	-31%	-14%
	Tue	10. Mrz.	24. Mrz.	-11%	1%	-14%	-13%	-11%	-14%	-4%	-10%	-5%	-15%	0%	-36%	-15%	-5%	-15%	-18%	-8%
	Wed	11. Mrz.	25. Mrz.	-6%	-4%	-7%	-14%	2%	-11%	3%	-7%	2%	-11%	13%	-23%	-22%	-9%	-13%	-4%	-3%
	Thu	12. Mrz.	26. Mrz.	-6%	4%	6%	-8%	-1%	-8%	9%	3%	8%	-8%	3%	-17%	-16%	-7%	-1%	21%	-1%
	Fri	13. Mrz.	27. Mrz.	-11%	-5%	4%	-1%	7%	-9%	1%	5%	9%	-1%	3%	-2%	-15%	-5%	3%	55%	-2%
	Sat	14. Mrz.	28. Mrz.	-13%	-2%	-2%	-3%	-2%	-5%	-9%	-3%	1%	0%	8%	3%	-8%	-8%	2%	40%	-5%
13 Days	Mon	16. Mrz.	29. Mrz.	-7%	-12%	3%	-9%	2%	-9%	-18%	-10%	-11%	-2%	13%	-5%	-12%	-15%	-12%	16%	-7%
	Tue	3rd 17. Mrz.	30. Mrz.	-1%	-5%	18%	-2%	0%	-7%	-1%	-8%	-15%	-3%	8%	8%	-5%	-7%	-16%	-22%	-4%
	Wed	18. Mrz.	31. Mrz.	-2%	-8%	26%	6%	4%	-12%	6%	0%	-14%	-3%	-6%	-2%	-2%	0%	-16%	-14%	-3%
	Thu	19. Mrz.	1. Apr.	-4%	1%	8%	17%	1%	-4%	10%	2%	-7%	4%	-12%	18%	4%	7%	-10%	-11%	0%
	Fri	20. Mrz.	2. Apr.	-7%	-3%	-6%	9%	-3%	-3%	-7%	-4%	-8%	2%	-1%	-3%	4%	-2%	-7%	-8%	-4%
	Sat	21. Mrz.	3. Apr.	-1%	1%	-13%	7%	-2%	10%	-3%	0%	1%	6%	6%	30%	9%	0%	11%	-12%	0%
12 Days	Mon	23. Mrz.	4. Apr.	-1%	-7%	-5%	3%	1%	0%	0%	2%	-3%	-8%	-4%	3%	7%	-5%	12%	-16%	-2%
	Tue	4th 24. Mrz.	5. Apr.	0%	-5%	-15%	14%	4%	11%	8%	4%	10%	-7%	-8%	65%	11%	3%	12%	-5%	1%
	Wed	25. Mrz.	6. Apr.	-3%	-6%	-10%	9%	3%	4%	2%	2%	7%	-9%	-3%	31%	2%	0%	-2%	-1%	-1%
	Thu	26. Mrz.	7. Apr.	-6%	1%	-14%	2%	-2%	8%	-1%	4%	12%	-3%	11%	50%	2%	4%	10%	9%	-1%
	Fri	27. Mrz.	8. Apr.	-10%	-1%	6%	-14%	-5%	-9%	-6%	2%	-1%	-5%	9%	-26%	-10%	-8%	7%	-9%	-5%
	Sat	28. Mrz.	9. Apr.	-12%	1%	-8%	-13%	-6%	-12%	-4%	-2%	-4%	-10%	-4%	-4%	-14%	-10%	4%	3%	-7%
11 Days	Mon	30. Mrz.	10. Apr.	-9%	2%	-11%	-10%	-4%	-13%	-6%	-7%	-6%	2%	-5%	-16%	-15%	-18%	-14%	5%	-6%
	Tue	31. Mrz.	11. Apr.	1%	13%	-32%	-4%	-1%	9%	3%	1%	-5%	12%	-4%	49%	8%	65%	-10%	45%	3%
	Wed	1. Apr.	12. Apr.	11%	5%	0%	-8%	2%	8%	10%	10%	0%	22%	-5%	23%	23%	61%	-3%	12%	6%
	Thu	2. Apr.	13. Apr.	16%	9%	13%	7%	6%	16%	17%	14%	4%	5%	-6%	51%	27%	66%	11%	34%	10%
	Fri	3. Apr.	14. Apr.	19%	7%	31%	13%	18%	8%	18%	15%	18%	13%	7%	44%	24%	-19%	17%	8%	14%
	Sat	5th 4. Apr.	15. Apr.	19%	19%	10%	35%	22%	29%	18%	14%	22%	3%	26%	91%	24%	5%	41%	57%	20%
10 Days	Mon	6. Apr.	16. Apr.	22%	16%	19%	24%	27%	33%	24%	20%	28%	23%	38%	66%	41%	17%	46%	24%	23%
	Tue	7. Apr.	17. Apr.	16%	11%	11%	17%	18%	33%	16%	17%	15%	-3%	32%	22%	22%	30%	47%	10%	16%
	Wed	8. Apr.	18. Apr.	8%	3%	24%	-8%	17%	7%	1%	6%	19%	11%	27%	-9%	15%	-6%	10%	-14%	9%
	Thu	9. Apr.	19. Apr.	-4%	4%	5%	-4%	3%	-9%	-24%	-6%	2%	-7%	10%	-7%	-10%	-10%	-5%	-14%	-2%
	Fri	10. Apr.	20. Apr.	-18%	-6%	11%	-8%	-11%	-22%	-23%	-17%	-7%	8%	-5%	10%	-7%	-13%	-17%	-8%	-12%
	Sat	6th 11. Apr.	21. Apr.	-18%	-9%	-6%	1%	-28%	-11%	-15%	-18%	-26%	-12%	-27%	-9%	-17%	26%	-7%	-26%	-18%
	Sun	12. Apr.	22. Apr.	-15%	-18%	-9%	-13%	-27%	-11%	-5%	-20%	-24%	-6%	-27%	-10%	-15%	14%	-18%	0%	-19%
	Mon	13. Apr.	23. Apr.	-4%	-16%	-18%	-1%	-21%	-6%	-12%	-14%	-19%	-14%	-20%	-40%	-20%	13%	-21%	26%	-14%
	Tue	14. Apr.	24. Apr.	-6%	-17%	15%	-2%	-12%	-12%	-5%	-13%	-11%	12%	-12%	11%	-8%	-7%	-29%	71%	-10%
	Wed	15. Apr.	25. Apr.	0%	-15%	19%	20%	-9%	3%	10%	-1%	-7%	4%	-15%	9%	-10%	-13%	-8%	52%	-6%
	Thu	16. Apr.	26. Apr.	-3%	-4%	22%	-2%	-5%	9%	24%	2%	0%	13%	-5%	44%	5%	-14%	-14%	91%	-2%
	Fri	17. Apr.	27. Apr.	2%	-1%	-17%	-1%	-1%	15%	13%	12%	2%	-4%	5%	-3%	-2%	-13%	1%	50%	1%
	Sat	18. Apr.	28. Apr.	-8%	-1%	-2%	-20%	12%	-1%	-3%	5%	1%	5%	14%	3%	3%	-6%	-11%	65%	0%
	Sun	19. Apr.	29. Apr.	-10%	1%	5%	-6%	15%	-14%	-7%	4%	-5%	1%	-3%	-21%	-12%	-8%	3%	-19%	-2%
	Mon	20. Apr.	30. Apr.	-16%	10%	14%	-23%	12%	-24%	-6%	-8%	-10%	-1%	-15%	-6%	-12%	-11%	-9%	-23%	-5%
	Tue	21. Apr.	1. Mai.	-8%	21%	-16%	-24%	1%	-6%	-13%	-4%	-14%	-8%	-17%	-9%	-25%	68%	2%	-49%	-2%
	Wed	22. Apr.	2. Mai.	-4%	10%	-17%	-21%	-4%	13%	-21%	-14%	11%	-11%	-6%	8%	-1%	89%	-10%	-24%	-2%
	Thu	23. Apr.	3. Mai.																	

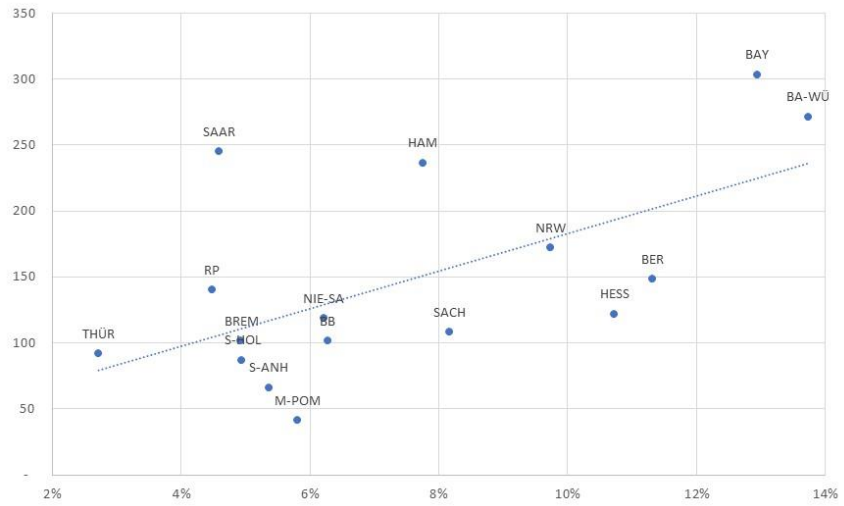
3.2.1 First bundle 02-06 March: End of carnival and winter vacation season

Figure 6 shows how the Rta values were decreasing across 13 out of 16 German states during this first week of March. There are subtle differences among the onset of the decrease between the states which are important, because they point towards how a natural calendar event reduced the Rta – which was the end of the main winter vacationing season. The details on how this lifestyle choice differs between the states are explained in Supplement I f) and in some case studies in Supplement V.

That winter sports in the Alps represented a strong super-spreading activity is amply proven by case tracing throughout all of Europe, and is also clearly evidenced by several of the regional case studies in Supplement V in the large German winter-vacationing states and counties. The natural end of the season meant that Rta dropped to a level of around 1 by the end of the week for most large winter vacationing states. The significant exception was Bavaria, which remained at an Rta of 2 because winter vacationing continued there due to geographical proximity. In the non-winter-vacationing states, which were barely infected at the beginning of March, the Rta stayed around 1.5, though the latter value is highly uncertain due to the very low numbers of confirmed cases at the beginning of March in those states.

Figure 7 shows the link between winter-vacationing in the Alps and covid-19 infection rates per state. The correlation coefficient is 61%.

Figure 7: Engagement in alpine winter sports and per capita infection rates per state



Unit of y-axis is # of infected per 100k population. Unit of x-axis is the share of active Alpine winter vacationers in the population per state. r = 0,61.

>> Engagement in winter vacationing is strongly correlated with the infection rates per capita in each state. This is a lifestyle choice driven by both tradition (Hamburg, NRW, Hesse, Berlin) and geographical proximity (Bayern, Ba-Wü, Saxony).

Source: Own calculations based on a report by German Sports University Cologne[20] on how many persons are actively engaged in alpine winter sports per state

3.2.2 Second bundle 07-10 March: Voluntary social distancing behavior

The second bundle of social distancing was not mandated by public policy, but emerged voluntarily by actions of private individuals and companies as a response to the increasing news coverage on the corona crisis. There had been continuous coverage on the Chinese situation throughout February, but at that time it was still a distant event for Western societies and observers. Global media attention increased eightfold from 200,000 daily news stories before 23 February to a peak of 1.7 million daily news stories on 17 March [21] (Figure 8). The virus had arrived in Europe. In addition, Monday 09 March experienced a historically large melt-

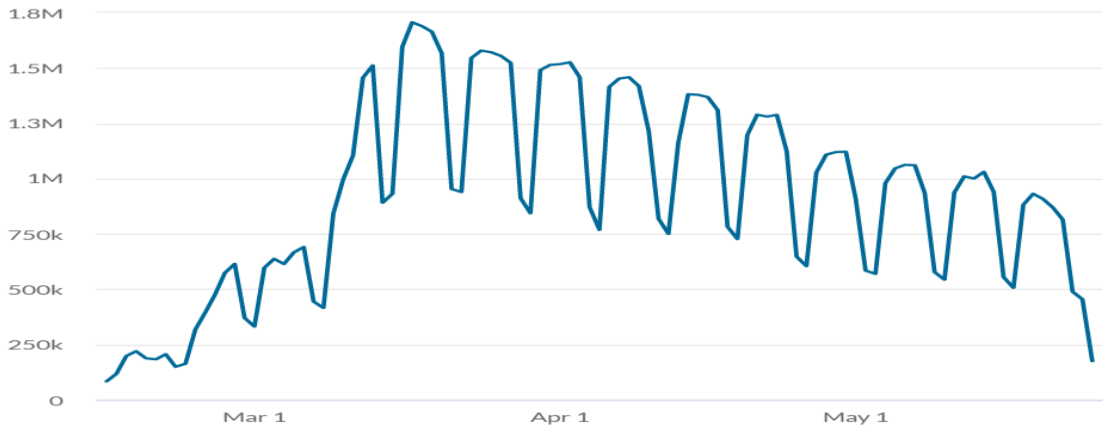
down of global stock market indices and the collapse of oil prices after Saudi Arabia and Russia failed to agree on a deal to cut production.

The impact on private and business behavior all across Europe was immediate. Planes, trains, hotels, restaurants and cinemas emptied out, snarling traffic jams in big cities disappeared. Enterprises swiftly recommended a non-handshake policy, disinfectant stations were set up, and home office was encouraged. The same happened throughout Germany as well. It was during this week, when all parameters in Apple's mobility tracking for Germany, mass transit, driving and walking began to rapidly decline by around 30% [22].

This second bundle is the only bundle which had a relatively uniform and large-scale effect in reducing the Rta across all states. It is the bundle with the lowest standard deviation of 5% and a mean of -15% Rto reduction per day (Figure 1). Moreover, by Wednesday 11 March, all states except Bavaria reached an Rta of at most 1 or as low as 0.6 (Figure 5).

Figure 8: Daily global news coverage of covid-19 crisis

Unit of y-axis is # of mentioning of corona- or covid-19 crisis in articles in global media.



Source: Lexisnews

3.2.3 Third bundle 16-19 March: Mandatory social distancing via shut-downs

With the benefit of hindsight we can now know that the Rta of the epidemic had already fallen well below a level of 1 by the end of the second week of March (Figure 5), and that, moreover, most super-spreading activity had been eliminated in the Alps, with the end of carnival festivals and cancellation of all other large-scale events. However, the political decision makers could not know this in the second week of March. All they could see was an alarming pace of newly confirmed cases, an increasingly panicked population as evidenced by emptying supermarket shelves, and expert advice from epidemiologists that a surge wave of infections must be avoided at all costs, or else witness the conditions in Northern Italy or Wuhan, where hospitals could not cope anymore. This is when the German national government formulated its first bundle of public policy for mandatory social distancing (MSD).

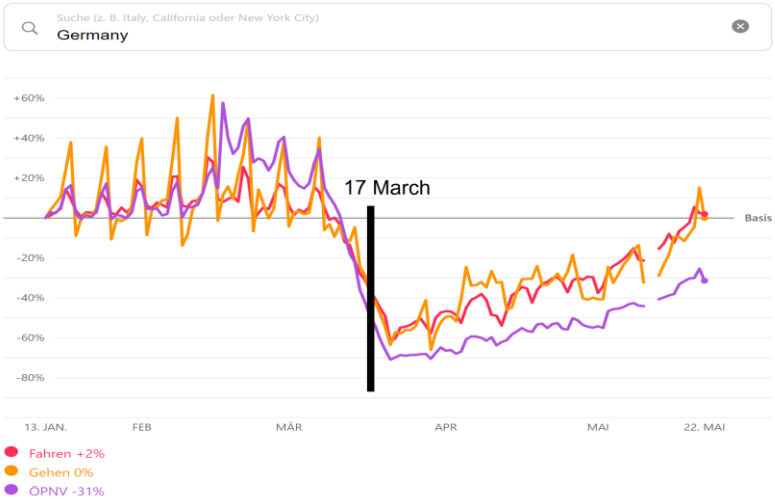
The bundle went into force from Wednesday 18 March onwards (for education it was Monday 16 March). The bundle meant de facto a shutdown of most public life. This bundle closed all education, entertainment, leisure, sports and religious facilities and prohibited any private meetings for such purposes. It closed all shopping stores except for essential items (such as

food, pharmacy, news stands, gas stations, pet shops and DIY/garden centers). It disallowed any tourism activity and restricted restaurants in their operations (but kept them open) [23].

On 17 March, the day before this public policy bundle became effective, Apple's mobility indicators for Germany had reached 64%, 51% and 62% for driving, mass transit and walking respectively. For the next ten days they dropped to and would hover around 48%, 32% and 44% respectively, and thereafter increased again steadily. Thus, around 70% of the mobility reduction observed in German society had been voluntary before this public policy went into force (Figure 9).

Besides achieving relatively little in terms of mobility reductions, this first national bundle of MSD measures cannot be considered to have had a systematic impact on the dynamics of the epidemic. In 4 out of 16 states, the Rta increased after its introduction. In several others there was no change, and in the remainder there was at best a mild reduction in the Rta (Figure 6). In numbers, it achieved a daily reduction in Rta of just 3% per day with a large standard deviation of 7% (Figure 1).

Figure 9: Change in mobility in Germany according to Apple mobility data



Unit of y-axis is the number of times that a request for directions was entered into an Apple map service. Apple seems to believe this is the best way to measure mobility. Note that this measure does not capture regular commuting or shopping as this would not usually be asked for in directions.

>> By the time the first MSD bundle was enforced, most mobility reduction was already voluntary.

Source: Apple.com

3.2.4 Fourth bundle 16-19 March: Mandatory social distancing via contact-bans

The second mandatory bundle came to be known as being the "contact-bans" (*Kontaktsperre*). This bundle closed all restaurants, cafés, bars and most DIY/garden centers, closed down all personal service providers such as hair salons, and allowed travel only for urgent business or other unavoidable purposes. Going to work was explicitly permitted, and all industries not directly affected by the closures were encouraged to continue. While Germans were allowed to leave their residences freely (no house arrest as in Italy, France or Spain), they were not allowed to be in groups of more than two persons outside of their own household, and were strongly discouraged to visit other households. A distance of 1.5 meters was to be kept to persons outside of the own household at all times.

As Figure 6 shows, just as with the previous MSD bundle, it cannot be considered to have had a systematic impact on the dynamics of the epidemic. In 10 out of 16 states, the Rta was increasing after the policy became effective. Even in Bavaria which triggered this bundle, the effect was neutral. On average the Rta increased by 1%, with a wide standard deviation of 5% (Figure 1).

3.2.5 Fifth bundle 03-07 April: First summer-like temperatures

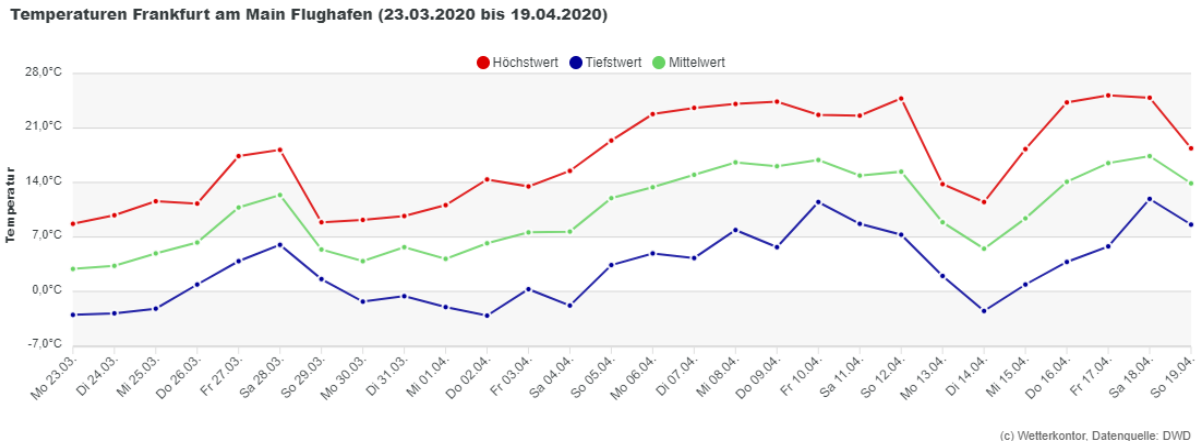
The weekend of 04/05 April brought the year's first summer-like temperatures of above 20 degrees C°, and forecasts suggested the good weather would remain throughout the week until Easter (Figure 10). As Germans were not under house arrest, they took to the streets and the countryside en-masse. Apple's walking parameter jumped to 59% on the Saturday, to 75% on the Sunday, and hovered around 68% for the remainder of the week.

There is little data on what kind of activities Germans undertook on this weekend. A survey conducted by the *Mannheimer Corona Study* [24] shows how the number of contacts with friends, relatives or colleagues began to increase substantially from that weekend onwards. The same study also shows that while support for the contact-bans had been around 60% on 20 March, the day they were decided in Bavaria, that value quickly dropped to around 35 % by Friday 03 April.

While the Rta had languished around 0.7 throughout most states during the previous two weeks, it jumped as high as 2. Figures 5 and 6 show that there was a tendency for the less infected states to reach higher Rta values and higher growth rates of these Rta. This seems to indicate that people who had less private or public exposure to the disease in low-infected states, then engaged in riskier behavior.

Uniformly across all states, the Rta was rising, at an average rate of 21% per day, with a standard deviation of only 8% (Figure 1). Some of this rise is due to a statistical artefact which is explained in more detail below in section 3.3. Regardless of which behaviors caused the rise in infections, it can be concluded that the public policies of shut-downs and contact-bans, which was in full force during that weekend and the following week, was not effective in preventing this uniform increase in Rta levels.

Figure 10: Temperature rising above 20 C° in Germany from April onwards



Source: Wetterkontor

3.2.5 Sixth bundle 03-07 April: Easter holidays

The sixth bundle of measures was due to another natural calendar event, in this case the event of Easter holidays, which in Germany is a 4-day public holiday weekend from Friday to Monday.

This holiday led to a uniform reduction of Rta across all states. Just as with the fifth bundle, there is no data that explains which behaviors led to the fall in the Rta, and it also is partially the result of a statistical artefact explained below in section 3.3. In terms of reducing the Rta the sixth bundle led to a minus 11% daily reduction of the Rta at a standard deviation of 8%.

3.3 The unexplained fall in the case identification rate

It appears that during the first two weeks of April, Germans with symptoms increasingly refrained from testing. Before Easter, the identification rate had reached around 1 out of 7 infections, but after Easter this rate halved to around 1 out of 14 (on the assumption of the Gangelt IFR). The reasons for this can only be speculated about. It may be related to a different public policy tool, which mandates at least two weeks of self-isolation at home for proven infected cases and quarantine of two weeks for all contact persons such as household members, colleagues at work, friends etc [25]. In Germany, the standard policy is to let patients stay at home, unless they need intensive care treatment in hospital. Since no treatment or medication is available, there is little benefit to obtaining a test unless one needs hospitalization, which can be arranged immediately when necessary. However, a positive test result has the negative effect of the whole household being forced to isolate at home and being stigmatized.

The deterioration in the discovery rate is calculated from the number of deaths that were recorded until 06 May, which is the last day on which numbers were included for the analysis of this article. Deaths during the first week of May must be related to cases that were confirmed two to three weeks earlier. But the number of dead did not decrease as fast as the number of confirmed cases after Easter, which is also clearly visible in the official numbers published by RKI [26]. Unless the mortality went up, for which there is no reason to believe so, or the case demography became much older, which was not the case, or the deaths counting methodology changed, which also was not the case, the only other possible reason for the reduction in cases is that the discovery rate went down.

The implication is that going forward, the confirmed case numbers become an even less reliable way to measure the progression of infections. This may impede the precision with which the epidemic can be monitored.

On Monday 20 April, the first small steps to loosen mandatory social distancing were allowed in Germany, primarily letting shops up to 800 sqm in size to open. Over the following weeks many different measures were loosened, and were implemented in different degrees across the states. The investigation of those impacts on the Rta needs to be the subject of a different study. The data realm of this study ends with the third week of April.

3.4 Overall interim conclusion on the six bundles of social distancing

There were three bundles of social distancing measures which had a uniform effect on the Rta throughout all 16 states. None of the three were due to a public policy. The first voluntary bundle, which was the second bundle overall, was the most effective of all of them to reduce

Rta. It was mostly characterized by a strong voluntary reduction in mobility, keeping distance in public spaces, and installation of home offices, where possible. The second voluntary bundle (fifth overall) resulted in the opposite. Despite legally enforced mandates of social distancing, the Rta multiplied in response to the first summer-like weekend in April, and a growing lack of public acceptance of the shut-downs and contact-bans.

The first and sixth bundles were automatic responses of society to two natural calendar events. The first was the natural end of the carnival-related holiday season which stopped the super-spreading activities of carnival and winter vacation in the Alps (except in Bavaria), and the last bundle was the Easter holiday weekend. Both bundles were well effective in reducing the Rta.

None of this analysis shall imply that social distancing as such is not effective in containing the covid-19 epidemic. But it does say, at least within the German context, that it is not necessary and possibly even counter-productive to mandate social distancing as a public policy. Voluntary responses by society and natural events were sufficient to achieve an Rta of around 0.7 on a sustained basis.

A counter argument could be made that the reasons the public policies failed to succeed is because they were not severe enough, and were not policed enough. This may or may not be the case, but the German data do not provide a good answer, because no house arrest was mandated as in other countries. The two public policy bundles were slightly more severe in Bavaria, but there is no indication that this led to different social behaviors, or for that matter different outcomes in the progression of the epidemic. In a few places, for instance in Mitterteich and Gangelt, cities were put under a more stringent form of quarantine. But as the case studies in Supplement V show, these sets of measures did not prevent the epidemic from spreading and contaminating their surrounding regions.

4. Tyrol and Bavaria as the Origin of the European Outbreak in December 2019 – a Proposal

The data in Section 3 speak in clear language that mandatory social distancing (MSD) was not effective as a public policy in the German context. There may be several reasons for this. It is proposed that public policies were not targeted specifically enough to inhibit dangerous social activities, due to incomplete knowledge about how SARS-CoV-2 transmits itself in communities. For learning more about these transmission routes, it would be helpful to understand the history of the epidemic better. For this purpose, this section combines an in-depth view of the data on German and Austrian excess mortality, influenza monitoring data and genetic mutation history, to propose a hypothesis on the first three months of the European outbreak from December 2019 to February 2020.

The proposal is that the Austrian state of Tyrol and the German state of Bavaria were the original epicenter of the covid-19 outbreak in Europe, with undetected infections numbering in the tens of thousands already towards the end of December 2019. From there it spread via the European fashion industry into Northern Italy, three Northeastern regions of France, Spain and New York City in early February, before returning to the Alps in late February. From the Alps it spread into all winter vacationing countries of Northern Europe. The reason why this outbreak could remain undetected for three months is because both Germany and Austria had been hit by a particularly strong influenza season in 2017/18 with high rates of excess mortality in February 2018. This contributed to a high average five-year number as a reference for expected mortality. It seems that the covid-19 epidemic was hiding in the shadow of this high average on the one side, and a weak influenza season 2019/20 on the other side, so that authorities did not notice unusual epidemic activity until it was too late.

The evidence for this proposal is presented here, and extensively in Supplements III and IV.

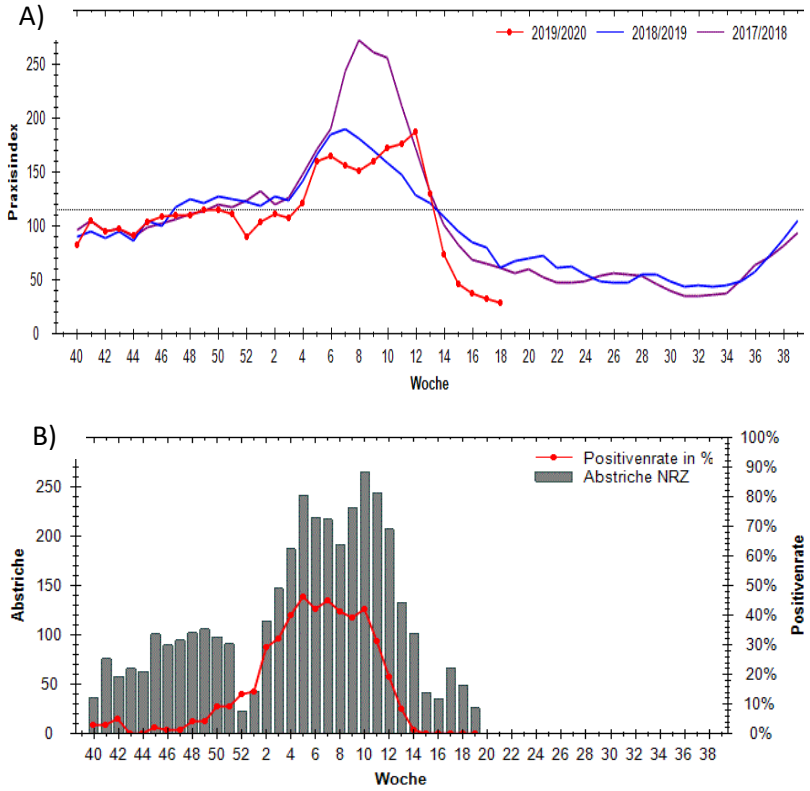
4.1 Irregular patterns in the German and Austrian excess mortality data

On 30 April, the German federal statistics agency published a special report on mortality per state over the past five years up to 05 April [27], which informs the following analyses.

During CW 8 of this year, which was 17–23 February, something uncommon began to kill people in Germany. The corresponding data are shown in Figure 2 in the summary section of this article, where excess mortality against expected trend begins to rise sharply from CW 8 onwards.

Classic influenza cannot be blamed for being the killer. The German 2019/20 winter was the second warmest winter on record (after 2006/7), clocking in at 3.9 degrees Celsius above average. It also had the least amount of snow, ice or frost days on record [28]. As a result, Germany was headed towards a record mild influenza season, as the German influenza monitoring system shows (Figure 11 A). This changed during CW 8 when patients began to rush into doctors' offices. However, the flu swabs came back negative, no particular increase in influenza case load could be detected at the national reference center (NRZ), indeed rather a decrease (Figure 11 B).

Figure 11: German influenza monitoring



A) Unit of y-axis is an index of patients visiting doctors for influenza symptoms, aggregate for Germany. Unit of x-axis is calendar weeks.

B) Unit of left y-axis is the number of swabs tested in the NRZ, the national reference center, per week. Unit of right y-axis for the red line is the rate of positives.

>> The 2019/20 season stayed mild below the number of symptoms of 2018/19, which in itself was mild against the strong influenza season of 2017/18. This trend changed in CW 8, when German patients went increasingly to doctors for influenza symptoms, peaking in CW 12 (16-20 March). While the number of swabs increased, the rate of positives went down. The influenza symptoms were caused by another disease.

Source: Robert Koch Institut Arbeitsgemeinschaft Influenza

Figures 2 and 12 employ a difference-in-differences method for comparing excess mortality state by state. For 2020, expected cumulative deaths are predicted on the basis of week-by-week trends derived from three previous years: 2016, 2017 and 2019. A declining curve means that states were undershooting the trend of those three years, a straight curve means they were exactly on trend, and a rising curve means they were overshooting the trend. Figure 12 shows how the German states were experiencing much lower mortality compared to the average of 2016, 2017 and 2019 until CW 7 (not even including the strong season 2018). Then the trend flipped, and people began to die at increasing rates compared to the previous years.

Figure 13 shows the same with a different set of numbers, this time comparing the German states' relative mortality numbers week by week against the average of the past three years, this time including 2018. During CW 8, mortality was 14% below average of the last three years at 86%. Six weeks later, in the first week of April, mortality was 6% higher than the average.

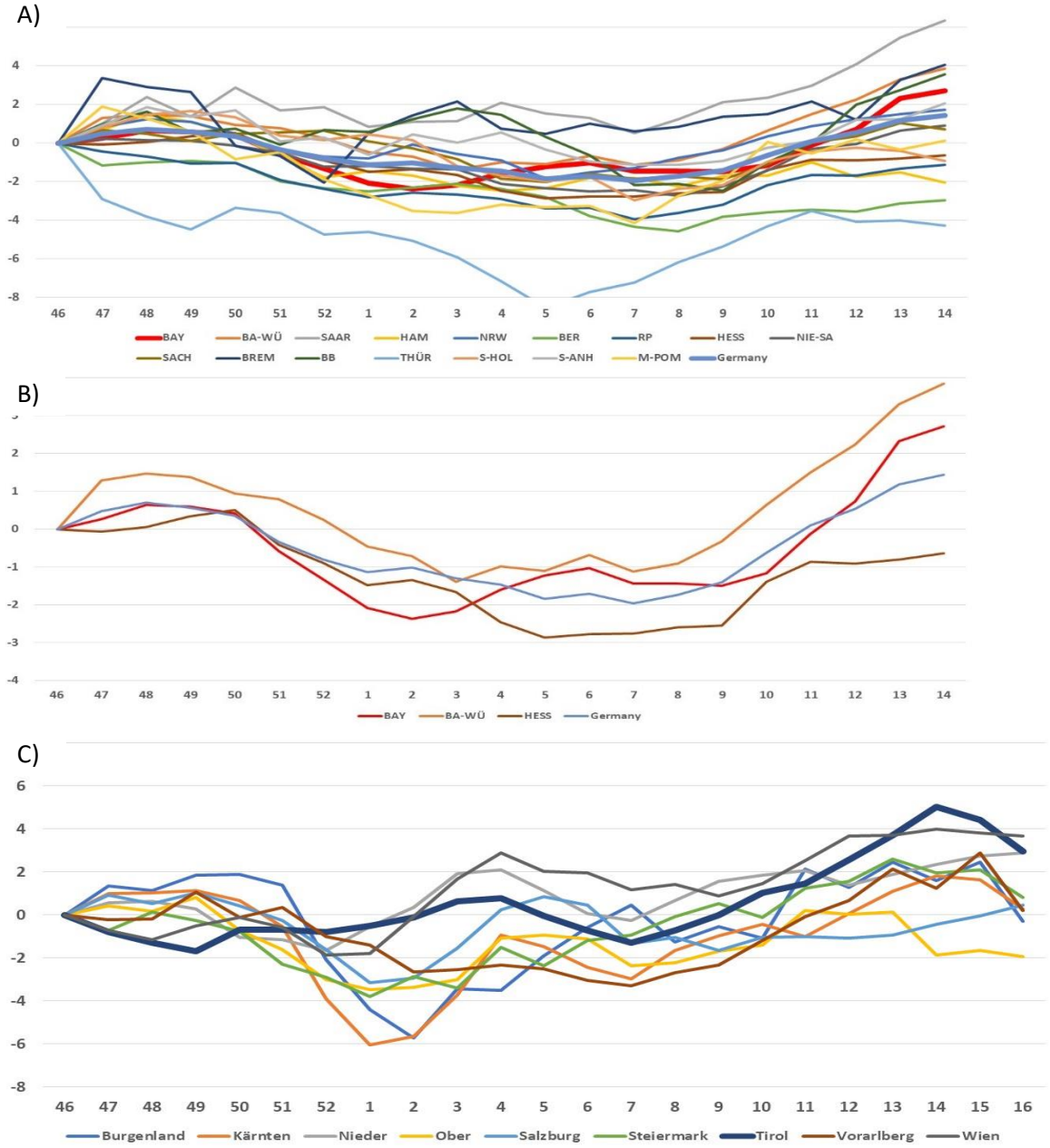
Since it was not the seasonal flu, and in the absence of any other known cause, an undetected outbreak of covid-19 must be the prime suspect of causing the sudden increase from 86% to 106% of the average. As Figures 2 and 12 B) show, in Bavaria this trend of excess deaths already flipped in the third week of January. Covid-19 must have been spreading around Bavaria from early January onwards, and cause mortality from CW 3. Most of Germany followed around five weeks later, with people being infected in significant scale in the beginning of February, and producing excess deaths towards the end of February. This would have been two weeks before the first covid-19 death was officially confirmed.

Figure 12: Difference-in-differences excess mortality by German and Austrian states

Unit of y-axis is # of persons per 100,000 population. The horizontal 0 line represents the average expected mortality on the basis of three previous years 2016, 2017 and 2019 per calendar week. The lines per state represent excess (above the 0 line) or deficit mortality (below the 0 line) versus their own respective mortalities in those previous years. The calculations are cumulative with base 0 in week 46 in 2019.

A) all German states; B) zoom on states of Bavaria, Hesse and Baden-Wuerttemberg; C) Austria

>> There is some diversity in the mortality patterns of the German states, but generally the German average 2020 started off with a strong deficit mortality in the first seven weeks. From CW 8 mortality began to rise against trend. The Bavarian experience has a unique shape of first declining strongly, and then rising from CW 2 onwards. It shares the same pattern with all Austrian states except Tyrol, which maintains excess mortality versus its own history as well as the national average from CW 50 in 2019 onwards.

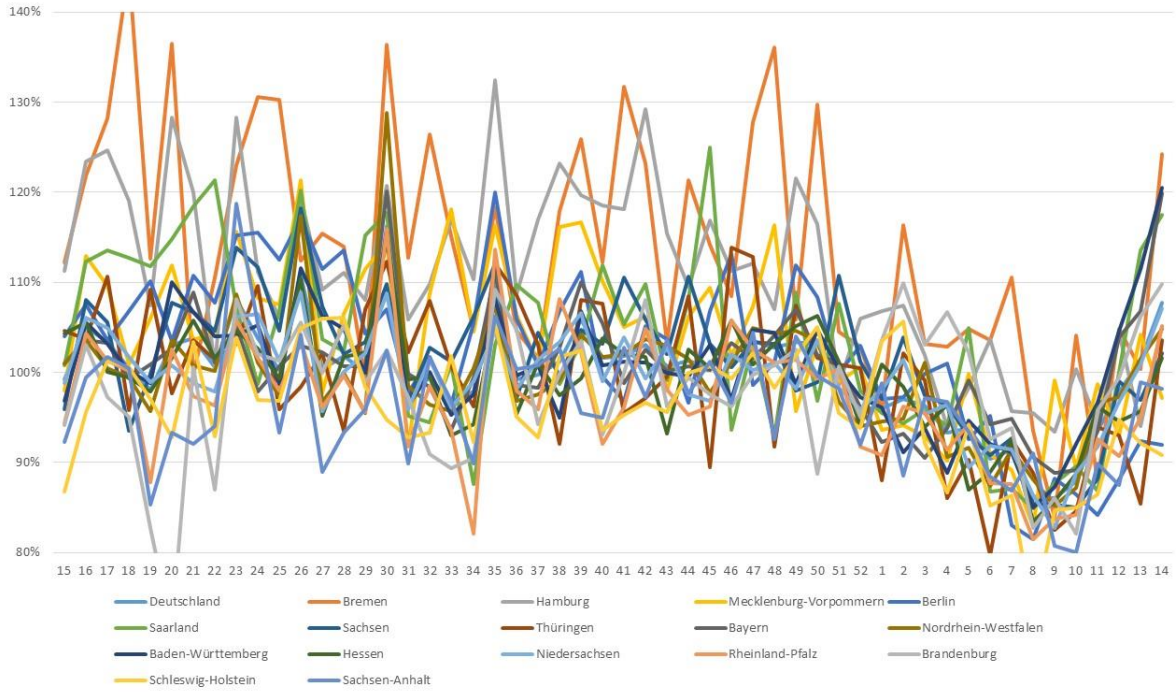


Source: Calculations for this article on the basis of official mortality data provided by the national statistics agencies: Destatis in Germany and Statistics Austria

Figure 13: German mortality relative to previous years

Unit of y-axis is percent relative to the previous three years. Units of x-axis are CW 15 2019 to CW 14 2020.

>> In the beginning of 2020, German mortality rapidly decreased compared to an average of the previous years. On an unrelated note: The state of Bremen had a high excess mortality throughout 2019, which is highly unusual. Mortality strangely spiked in CW 35 across all German states, as well as in many European countries.



Source: Calculations for this article on the basis of official mortality data provided by DeStatis

One could consider Bavaria to be a coincidental outlier in Germany. It is not abnormal for regions to experience unusual mortality patterns that may simply be stochastic. However, in Bavaria's neighboring country, the Austrian states follow the same pattern, as Figure 2 and 12 C) show: first a sharp decline of deaths after Christmas compared to previous years, then something begins to cause some Austrians in all states to die more often than usual from the second week of January onwards. The only exception is the state of Tyrol: its inhabitants began dying at an unusually high rate from the end of December onwards.

The unit in figure 2 is number of deaths per 10 million inhabitants per week. Tyrol has a population of 757,000 so this meant an additional 13 deaths out of a total of 137 deaths recorded in CW 2. A 10% anomaly is not something which local authorities would have been able to detect at the time. The same is true for Bavaria. Until CW 2, Bavaria was running at 200 deaths per 10 million inhabitants below the previous years, before mortality began to abnormally increase. In that second week, Wuhan in China was neither known nor in the news. There was no reason to suspect that a sudden rise in mortality from CW 3 onwards could indicate an incipient epidemic. But with hindsight, the data tell a clear story that something was afoot in Bavaria and Austria, and especially in Tyrol: covid-19 should be the answer.

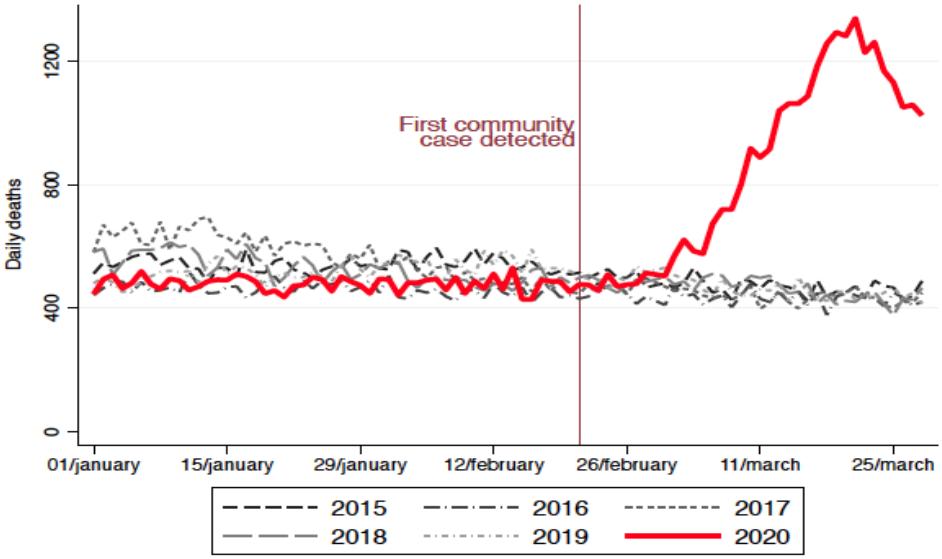
Italy provides detailed mortality data on a city level. Researchers at VOX CEPR conducted a similar difference-in-differences methodology to calculate when true excess mortality took off

in the North Italian cities [29]. The data show clearly that this happened from around CW 10, (02–08 March, Figure 14). That means Italy became infected two weeks after Germany, seven weeks after Bavaria and Austria, and twelve weeks after Tyrol.

Figure 14: Difference-in-differences excess mortality in early affected Italian cities

Unit of y-axis is daily deaths from registry data for a sample of 1,161 Italian municipalities in the seven regions most severely hit by covid-19 (Emilia-Romagna, Liguria, Lombardia, Marche, Piemonte, Toscana, and Veneto) and match them to census data to analyse covid-19-induced mortality. Overall, the dataset covers a population of almost 15 million inhabitants, roughly 25% of Italy's total.

>> In Italy's earliest affected cities, excess mortality only began from CW 10 onwards, two weeks after Germany



Source: Ciminelli and Garcia-Mandicó 2020 at VOX CEPR Policy Portal

4.2 The evidence from genetic mutation history for the Tyrol and Bavaria proposal

There is a second line of evidence which suggests Tyrol and Bavaria were the first dominant epicenter of the outbreak in Europe. An international consortium of researchers at GISAID has been compiling the genetic sequences of the mutations of SARS-CoV-2 from 20 February onwards [30]. By 14 May, around 24,000 of these sequencings had been done around the world and added to the publicly available database. About 1000 new strains are added per day. The phylogenetic dendrogram which is shown on the webpage nextstrain.org provides an overview on how the virus spread through time and place.

The methodology of the phylogenetic dendrogram and the evidence it provides for the Tyrol and Bavaria proposal is explained in extensive detail in Supplement III with 20 powerpoint charts shown in Supplement IV. Phylogenetic dendrograms are not self-explanatory. Understanding the evidence will require reading the entire Supplement III.

As was explained in the summary section and in the subtext to Figure 3 above (and is extensively explained in Supplement III), the phylogenetic analysis leaves no ambiguity that the European strands separated from the Chinese clades already at the end of November 2019 and must have caused a large and at the time undetected European outbreak in January and February. Thus, the European outbreak happened independently of and parallel to the

outbreak in the city of Wuhan and China. The genetic diversity across all European locations multiplies from February onwards (Figure 16). This means that the phylogenetic dendrogram indicates that from the European outbreak's early origin in late November on the so-called A2 clade, there was only one region during January where it developed. If this had been a Chinese region, then we would need to see many China-located mutations sequences on the A2 clade in January and February. However, there are only two of them, so it must have been a European region (the two Chinese mutations would be re-imports or they are wrongly assigned). This one single European region must fulfill three criteria:

a) Cases from this region should not be clustered on a later clade, because the place of the original outbreak should show the largest genetic diversity. This condition excludes France, Switzerland, Luxembourg and Spain as a possible origin, because they dominantly cluster on their own clades.
b) The region must have shown some medical symptoms of an outbreak during January, because if the virus was circulating, it must have caused disease and mortality. This condition excludes most European countries, such as the British Isles, Netherlands, Belgium, Italy, all of Scandinavia and Eastern Europe, whose members are spread across the entire dendrogram, but who did not experience excess mortality in January.
c) It must be a place to which or from where there is considerable European travel connection, and where there are large scale events that can act as super-spreader occasions.

The best-fitting European region for which all three criteria would be true for January is the Munich region of Bavaria in Germany, in connection with its neighbor Tyrol in Austria. Vienna could also be considered, but it is not a trade fair center like Munich is, and it is only half as connected to Europe as Munich.

4.3 Connecting the dots – A cautiously proposed reconstruction of the early days of the European covid-19 outbreak

This section is a cautiously proposed reconstruction of the events that might have happened when considering the evidence from Sections 4.1 and 4.2 together with the extensively detailed evidence provided in Supplements III and IV. It must be emphasized that while all this evidence coherently interlocks to support the proposal, most of it is nonetheless indirect. The smoking gun of primary direct evidence is still missing. However, with antibody testing or targeted case tracing in the locations mentioned, the proposal could be tested and either verified or rejected.

Stage 1: 01-06 December in Innsbruck, Tyrol, Austria

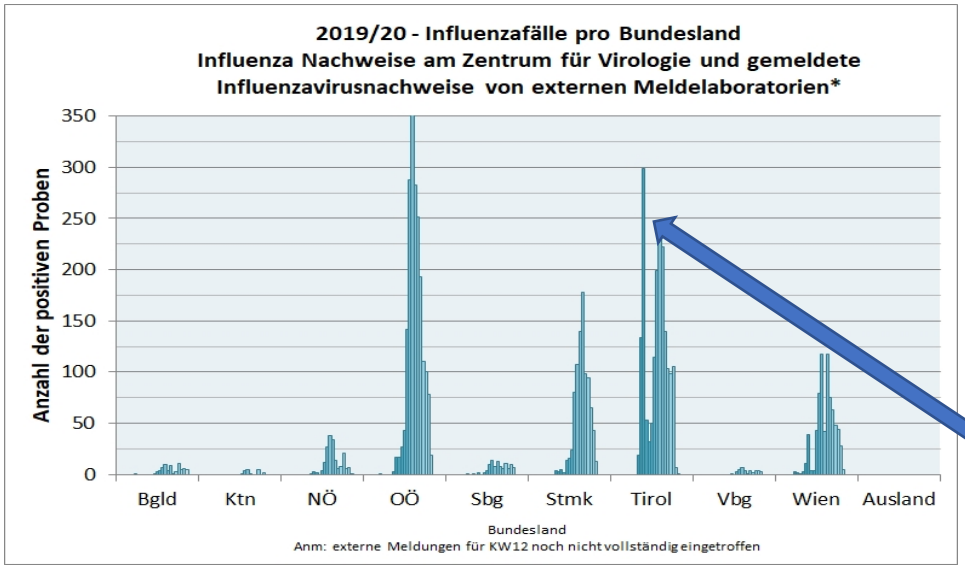
Santa Claus arrives in the city of Innsbruck on four separate occasions between 01 and 06 December. Two weeks later there is a highly irregular influenza outbreak recorded in the city and two elementary schools need to close. Unusually many obituaries are published in the following four weeks in Innsbruck newspapers.

Proposal: This was not an influenza outbreak as believed by the authorities, but a covid-19 outbreak in the city of Innsbruck in December 2019, and started by infected Santa Clauses. Around 45 persons may have died, with a total of around 10,000 infected, or around 7% of the Innsbruck population. The excess mortality of the state of Tyrol would be concentrated on its

capital alone. The Innsbruck outbreak would have faded away by mid-January without leaving descendants, were it not for the Four Hills Ski Jumping Tournament, which is covered in the next stage.

Evidence explained in Supplement III: local newspaper articles, influenza monitoring statistics, mortality statistics

Figure 15: Influenza statistics for Austrian 2019/2020 season



Units of y-axis are the number of positives for influenza testing, for each of the 9 Austrian states. Unit of x-axis are CW per state

Tyrol had a highly irregular outbreak in the two weeks before Christmas. There is no precedent in the previous ten years of influenza monitoring in Austria

Source: Austrian influenza monitoring at Medical University of Vienna

Stage 2: 03-04 January at the Four Hills Ski Jumping Tournament in Innsbruck

Phylogenetics suggests that there must have been a super-spreader event where the virus mutation of the A2 clade generated infection chains in several new geographies in CW 1 of 2020 (Figure 16), which did not fade away.

Proposal: The Four Hills Tournament is the world's largest and most prestigious ski-jumping event of the year, lasting for a week. The tournament receives 120,000 visitors. Innsbruck is the third out of four hills in the Alps. The Polish ski-jumping team is among the best in the world. The Polish sports fashion label 4F is one of the main sponsors of the Four Hills Tournament.

It is proposed that the Four Hills Tournament event in Innsbruck was the occasion where the virus forked off among the spectators into Bavaria and Austria. It may have also infected professional members of the Munich-area fashion industry (for instance models, stylists, event managers, journalists, designers etc) at some of the events sponsored by 4F.

If Austria and Bavaria became infected there, it would explain their irregular excess mortality in January and February, which sets them apart from the rest of Germany and Europe. If the mild influenza year of 2016 is taken as a reference, then In Bavaria up to 1400 persons died from the outbreak of this clade before it faded away by the end of February. In Austria the outbreak of this clade may have caused up to 1000 deaths before it faded away. No descendants of the early Bavarian and Austrian outbreak are known, except for the handful that went on to become super-spreaders at three different events in the beginning of February, which is the story of Stages 4, 5 and 6.

Another piece of incidental evidence is in Poland. The main winter vacation province and ski-jumping capital of Poland, Silesia, accounts for one third of all Polish covid-19 confirmed cases, and has a three times higher infection rate than the Polish national average. Unfortunately, Poland has not sequenced enough mutations to be able to link the Silesian epidemic experience to an early event in January in Innsbruck.

Evidence explained in Supplement III and IV: phylogenetics, newspaper articles, mortality statistics, covid-19 statistics

Stage 3: 28 January in the Munich region of Bavaria

The first detected European transmission case, an outbreak at the company Webasto in the Munich region in late January, sits on the A2 clade of the phylogenetic dendrogram (Figure 16). The case was detected because supposedly a Chinese business woman infected her German colleagues during business meetings at company headquarters in Stockdorf, 20 km out of Munich on 20 January, and later tested positive after returning to Shanghai.

Proposal: An unbiased reading of the extensively published case tracing details of this outbreak suggests that it was reverse: the German colleague infected the Chinese business woman. On this reading, the Webasto case would be direct evidence that the virus was widely circulating around the Munich region throughout January.

Evidence explained in Supplement III: Phylogenetic dendrogram, peer-reviewed scientific journal articles and published research from the Italian Sacco Hospital that concludes that the Italian Codogno case (detected 20 February) and the Webasto case must have a common ancestor in the Munich region in the middle of January

Stage 4: 26-29 January ISPO sports business professional trade fair

Phylogenetics suggests that there must have been a super-spreader event in CW 5 where multiple infected participants generated multiple infection chains in dozens of countries at once (Figure 16).

Proposal: Munich hosted the ISPO trade fair in CW 5. It is advertised as: “The largest trade fair for sports business. At ISPO Munich the entire sports world will gather again to shape the future in the segments Snowsports, Outdoor, Health & Fitness, Urban, and Teamsports. Look forward to four days with over 2,800 exhibitors and more than 80.000 visitors” [31].

It is proposed that this trade fair for sports business and sports apparel was the super spreading event of CW 5. Only a trade fair has the capacity to generate infections chains in many countries at the same time.

The first Italian case in Codogno on 20 February is a direct genetic descendant from this super-spreading event, if it was not Munich, then somewhere else. The first infected Italian, a 38-year old Unilever manager called Mattia is known to be very active in recreational sports [32]. So far it could not be identified how Mattia became infected.

Evidence explained in Supplement III and IV: phylogenetic dendrogram

Stage 5: 04-06 February Munich Fabric Start 2020 professional trade fair

Phylogenetics suggests that there must have been another super-spreader event in CW 6 in the same location as the one in CW 5, where a single infected participant generated multiple infection chains in dozens of countries at once (Figure 16).

Proposal: Munich hosted the Munich Fabric Start Trade Fair in CW 6, one of the key events in the global fabrics industry. The fair is advertised as: "About 1000 exhibitors from 40 countries present some 1800 collections and a comprehensive range of fabrics, trimmings and additionals, fabric finishing, full-packaging services and manufacturing thus ensuring the competence and professionalism required by more than 20,350 trade visitors for a perfect season opening [33]."

It is proposed that this trade fair for the global fabrics industry was the super spreading event of CW 6. Only a trade fair has the capacity to generate infections chains in many countries at the same time. Most of the Spanish infections are a direct genetic descendant from this super-spreading event.

One week after this Munich fair, the first covid-19 pneumonia cases are treated in the central hospital of Alzano, the city at the mouth of the Seriano Valley, Italy's fabric industry center, adjacent to Bergamo. So far it could not be identified, why Bergamo became the epicenter of the Italian outbreak.

Evidence explained in Supplement III and IV: phylogenetic dendrogram

Stage 6: 03-12 February Men's and Women's Fashion Week in New York

Phylogenetics suggests that there must have been a third and fourth super-spreader event in CW 6 and CW 7 successively, in which multiple infected persons generated multiple infection chains at the same time, but predominantly in the cities of Paris and New York only (Figure 16).

Proposal: The phylogenetic dendrogram is highly specific. There must have been two events only a few days apart, where most of the first Paris and most of the first New York infections happened simultaneously, but in almost no other regions besides these two. The first event must have happened in CW 6 and the second event in CW 7. Both events generated hundreds of infection chains. There are two events that can be imagined to offer such a possibility, which is first the Men's fashion show from 03-05 February, followed by the Women's fashion show from 06-12 February during the New York Fashion Week [34 35].

Four regions of France are the heaviest affected by covid-19. Haute France, Grand Est and Auvergne-Rhone-Alps account for one third of all confirmed covid-19 cases. The fourth, Ile-de-France (Paris) accounts for another one third. These four regions also account for three quarters of all employment in the French textile industry [36]. The first outbreak hotbed of France was in Oise Department. Its capital city Beauvais, 100 kilometers north of Paris is a traditional center of high-quality fabrics and tapestries, reaching back to Colbert and even centuries before then. So far it could not be identified why Oise Department was the first epicenter of the French outbreak [37 38].

Evidence explained in Supplement III: phylogenetic dendrogram

Stage 7: Back into the Alps and from there beyond

If the above proposals are right, then unknown and undetected in Europe, SARS-CoV-2 had been spreading around Europe's textile and fashion industry throughout February. Evidence linking the first North Italian cases to a common ancestor in Munich in January, was already established in early March by Italian researchers, but has since then been ignored. The first cases in Alzano in the Seriano Textile Valley close to Bergamo, seem to provide a further link to the textile trade fair in Munich. The inevitable tactile touching of fabrics and close interpersonal contact in the fashion industry, intensive socializing among closed groups in crowded events, and social expectations around physical appearance and health instead of admitting to a disease, should have created the perfect propagation grounds for the virus.

Under standard circumstances, the Munich region cluster would have probably faded away, just as it did in its likely ancestor in Innsbruck, and its cousin cluster in Austria. But by finding its way into the textile and fashion industry via trade fairs and fashion shows at the beginning of February, it caused infection activity to explode from there into all directions.

In parallel to the textile and fashion transmission path, the virus may have followed a few other routes to super-spreading success. From Munich the virus must have slowly spread around Germany. Germany has a different health care system than Italy. Whereas in Northern Italy, and Lombardy in particular, health care provision is centralized in large hospital centers, the German system is rather decentralized and relies on a widespread network of small-scale community doctors as a first response. In the course of February, these German community doctors saw a rising number of influenza-like-illnesses, which did not surprise them, as it was influenza season. They sent the patients back home and wished them well and in the vast majority of cases, this is exactly what happened. But for some of these patients, the unknown disease terminated their lives prematurely with embolisms, cytokine storms or non-bacterial pneumonias. Since Germany does not operate a centralized mortality registry, the clustering of such cases was not noticed. Even as mortality was rising from CW 8 onwards throughout Germany, there was nothing unusual in the numbers. Overall mortality was still below the expected average of the previous years. Yet in hindsight, mortality was rising against a trend otherwise driven by a weak influenza season and mild weather.

In the course of February, the fashionistas flocked to the Alps for winter vacationing, and increasingly infected the ski resorts and après-ski bars. The likely heavily infected Munich fashion scene did so primarily in the state of Austrian Tyrol and Italian province of South Tyrol, Germany's favorite places for a winter vacation. From the many Alpine ski slopes, and Tyrolian Ischgl in particular, the virus began to super-spread towards all other winter vacationing Europeans who would otherwise not have been in contact with the fashion industry, in particular the Germans, Swiss, Dutch, Belgians, British and Scandinavians, whose infections and mortality began to rise from the second week of March onwards. That Tyrol became a super-spreading region again, was pure coincidence. No direct descendant from the likely first Innsbruck outbreak has yet been found in the dendrogram. None of the winter-vacationing mutations link directly to Innsbruck, they do so only via the fashion industry clades, which appear to have been generated in just three super-spreading events, two of them professional fairs in Munich, and one being a fashion show in New York.

In parallel, likely radiating out from Northern Italy's world-famous textile industry, the virus circulated there throughout February and followed a different route to proliferate. While the Italian large health care centers are highly efficient, they are also often the primary care

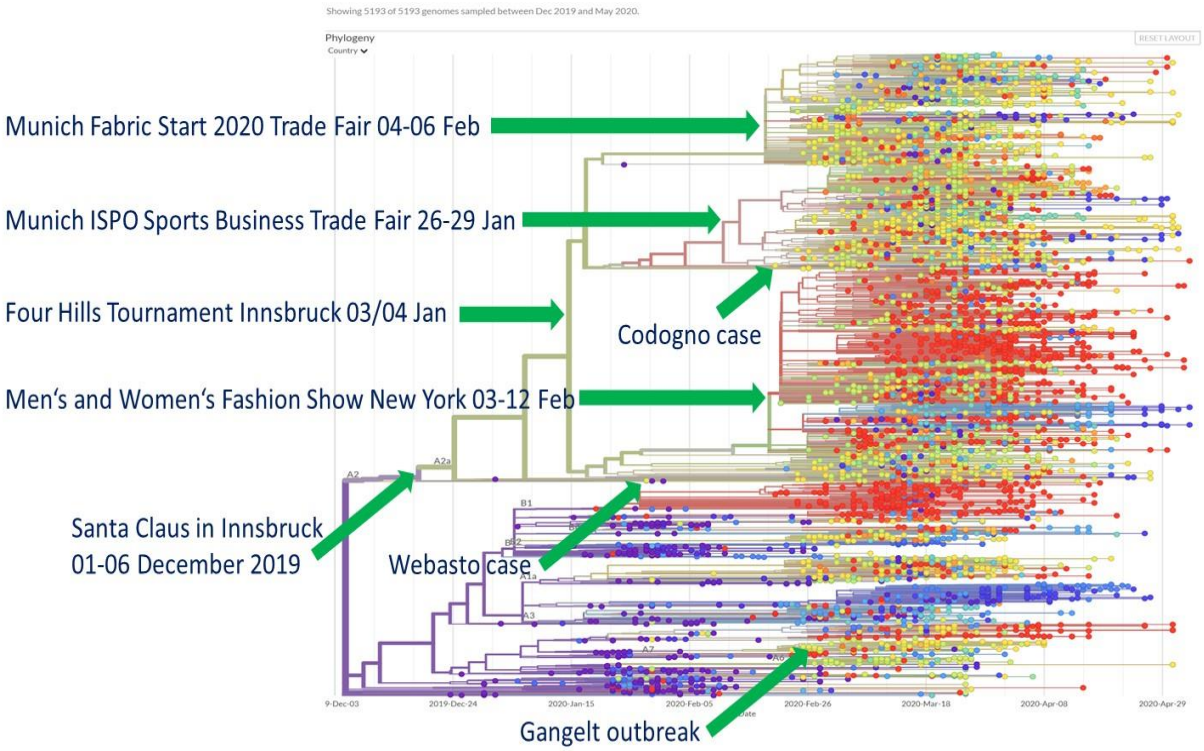
institutions and thus can easily become super-spreading places. When ill patients presented at hospitals, they were tested for covid-19 only if they had a China-background. Without a China connection, they could freely contaminate scores of staff, patients and other visitors. In this way, the crisis not only accelerated in Italy faster from the end of February onwards, but it also became visible earlier in Northern Italy. It was only after Italy became considered a risk area, that Germany began to test systematically those with contact to an Italian person. Just as with the Webasto case, it is not clear who infected whom. It may actually have been the Germans who infected the Italians in these early encounters. But it was only because of the outbreak having been noticed in Italy's large hospital centers, that Germany began to notice its own cases.

After the Spanish clades were possibly generated at the ISPO fair, Spaniards inadvertently created another route to super-spread the virus, namely by conducting large-scale women's rights demonstrations on 08 March in their major cities. Soon afterwards, Spain's health care system succumbed. France also has its own Alpine clade, reflecting the fact that the French visit their own Alps, and not the Austrian ones. France also conducted a nationwide election on 15 March which is known to have promoted the spread of the virus.

Incidentally, the mid-February outbreak in the German city of Gangelt in North Rhine-Westphalia was not related to any of the above. Its ancestors had infected themselves directly in Wuhan at the end of December, and do not belong to the European clade.

Figure 16: Proposed chain of super-spreading events leading to the European outbreak

In depth explanation on the phylogenetic dendrogram is provided in Supplement III and IV



Source: nextstrain.org

Some explanation on Figure 16: Only a few more than 5000 clades can be displayed at once. The algorithm of what is displayed changes over time. Differing subsets of data which are called up by the algorithm, also change some

timings of the clades and strain connections on the dendrogram. So the diagram will not remain looking the same as shown here on the charts in Figures 3 and 16, and in Supplement IV.

The date line on the x-axis is calibrated on the date of discovery or registration of the cases. Thus, the infection happened between 10 to 14 days earlier. Therefore, all dates must be offset by 10-14 days to the left.

Every dot represents one case being detected and its genetic sequence being recorded. The colors of the dots in this version of the dendrogram refer to geography where the cases are detected: purple is China, blue is Asia, green and yellow is European, red is North American.

Each horizontal line represents one clade, which corresponds to a particular mutation. The virus mutates at a specific constant rate, so that genetic distance between clades can be reliably ascertained. Assignments of individual dots to a particular clade may not always be reliable as some mutation patterns may make several assignments possible.

Vertical lines represent super-spreading events, indirectly inferred from many clades having a common time of origin from a single previous old mutation, thus creating a vertical line. If there were several infection chains operating at a single event, then this would look like a cascade as for instance at the Munich ISPO event. A cascade indicates a super-spreading event if each clade has the same genetic distance (cannot be seen on this chart).

Figure 16 shows clearly, as does Figure 3 in the summary Section, that around 80% of the European outbreak goes back to a single clade called A2, which forked off already at the earliest beginning in late November. The location of this first fork is generally assumed to be China, but there is no direct evidence of this. It could as likely have been a European location where Chinese persons from Wuhan (on business or tourists) became infected.

4.4 Conclusions of the mortality and genetic mutation analysis

Due to lack of data, there is no direct proof yet that Tyrol and Bavaria were the original epicenter of the European outbreak. But the indirect evidence is staggering. Both the excess mortality data and the genetic sequencing of mutations data interlock perfectly to point at the same conclusion, that this is where it all started for Europe, then the US and then the rest of the world. In parallel, there had been hundreds and maybe thousands of infections of Europeans directly in the China outbreak, partially directly in Wuhan, and partially in other Chinese cities or regions. Many of them led to significant infection chains. However, it was a single evolutionary clade called A2 with a mutation called D614G which overwhelmed Europe and then the rest of the world. It seems likely that this mutation was incubated somewhere in Europe, possibly in Tyrol. With additional primary data, such as antibody tests in the potential outbreak centers of Tyrol, the above proposed transmission chain of the early days of the epidemic can be confirmed or refuted.

It would be tragic if knowledge of the early transmission chains and outbreak centers would be used to stigmatize these regions, or the persons who became the super-spreaders. If they were the early centers of the outbreak, then this was not their fault. It was simply coincidence of being in the wrong place at the wrong time.

We should try and understand completely the early transmission chains in order to understand the transmission dynamics more generally and for the future. If the above hypotheses are confirmed, they indicate that SARS-CoV-2 has considerable difficulty to sustain itself in community transmission. It will fade out after just a few generations. For its continued propagation, the virus requires super-spreader events and/or super-spreading persons. There is no doubt that the virus leaves noticeable excess mortality in its path, so an effective public health response is required. Finally, the role of textiles in the transmission dynamics needs to be more carefully investigated.

5. The Mystery of Super-Spreading and the Failure of SEIR Models

A detailed look at the case studies in Supplement V of the German experience with the covid-19 epidemic raises numerous mysteries. For instance, on 15 February there was a carnival event in the village of Langbroich, a village of just 656 inhabitants, which is part of the city of Gangelt (population 11,634), which is part of Heinsberg county (population 254,000). A total of 320 people attended this carnival celebration on a single evening. Yet this one event became the starting point for an outbreak in the region which ultimately made the entire Heinsberg county one of the most infected areas in Europe, similar to Italian Lombardy, and the fifth most infected county in Germany. One week later, from 22 February, the neighboring city of Cologne, only 75 kilometers away, celebrated its carnival: a five day, non-stop party in a city with one million inhabitants. Cologne carnival has 1.5 million visitors from all around the world, which makes it a larger event than Mardi Gras in New Orleans. But the covid-19 case numbers do not show any appreciable infection activity during Cologne Carnival. On a per capita basis, even two months later at the end of April, rural Heinsberg county is still three times more infected than the metropolis of Cologne.

In another local outbreak, it seems most participants of a trombone orchestra concert in the village church of Kupferzell with 380 seats became infected on 01 March, which then subsequently made the surrounding Hohenlohe county (population 112,000) the sixth most infected county in Germany. At the same time, not far way, the metropolis of Frankfurt which has the busiest main train station in Germany, and has the third busiest airport in all of Europe, has the lowest case load of all major German cities, and on a per capita basis only about a quarter of the cases of the Heinsberg or Hohenlohe counties.

A third case: Wiesbaden and Mainz are twin cities, divided only by the Rhine river. They are of similar size (populations around 250,000), similar level of income, and both are capital cities of their respective states of Hesse and Rhineland-Palatinate. Both cities are highly interconnected on economic, social and cultural levels. One in two employees in the region crosses city and county boundaries to travel to work [39]. A tenth of the workforce of Wiesbaden comes from Mainz, and vice versa [40]. But Mainz has twice as many confirmed covid-19 cases as Wiesbaden on a per capita basis.

A fourth case: Tirschenreuth county in Bavaria (population 72,504) is one of the most sparsely populated and remote regions in Germany. Per capita, more people died of covid-19 in this county than in Italian Lombardy [41], and it is not yet known why. About 100 kilometers away, in Saalfeld-Rudolstadt county (population 106,356), not a single person died of covid-19.

Besides these and numerous other case studies like them, there is a large disparity of pandemic experience within Germany, which so far defies explanation. For instance, one quarter of all German cities and counties have infection rates that are just one third or even less than the German average. How can so many regions have such low infection levels?

5.1 The inadequacy of SEIR epidemiological models

The traditional SEIR model is the base engine of epidemiology and is also the usual default with which the covid-19 pandemic is commonly analyzed, with various degrees of sophistication. As just one example, an Italian team expanded SEIR into a SIDARTHE model which was published in Nature Medicine [42]. In the SEIR model, individuals in a community graduate from

being *Susceptible* towards being *Exposed*, then *Infectious* and then *Removed* – with respective transmission rates between these four stages, which can be separately specified by various variables and probability distributions. However, the SEIR model cannot be tuned to account for any of the above four case study comparisons. Any plausible variable settings for describing how individuals move from one stage to the other would fail for either high-infected Mainz or low-infected Wiesbaden, or would fail for either super-infected Heinsberg versus low-infected Cologne, Hohenlohe versus Frankfurt or Tirschenreuth versus Saalfeld-Rudolstadt.

Neither the SEIR model, nor any its more sophisticated derivatives, can fundamentally capture the above critical mass dynamics. SEIR models only differentiate between an exponential and a non-exponential growth state. In a dangerous exponential growth state, the disease will eventually sweep through a community in a surge, and in a non-dangerous non-exponential growth state it will fade out. Public health interventions main objective is to transition a community from the dangerous to the non-dangerous state.

However, as for instance well-documented Singapore has painfully experienced, this is not how the covid-19 epidemic seems to be developing. The Singapore experience is not characterized by exponential versus non-exponential growth as the SEIR model implies, but by lingering latency versus sudden explosion in super-spreading events. The SEIR model cannot account well for either long running lingering latency in the community, nor for a sudden explosion of cases. The entire European experience with covid-19 should be similarly understood. SEIR-based epidemiological models are structurally incapable of capturing these dynamics. The phylogenetic dendrogram shows that almost the entire European outbreak and most of the outbreak in North America can be traced back to just three super-spreading events in early February 2020. There is no amount of tuning of parameters that can make a SEIR model replicate this result.

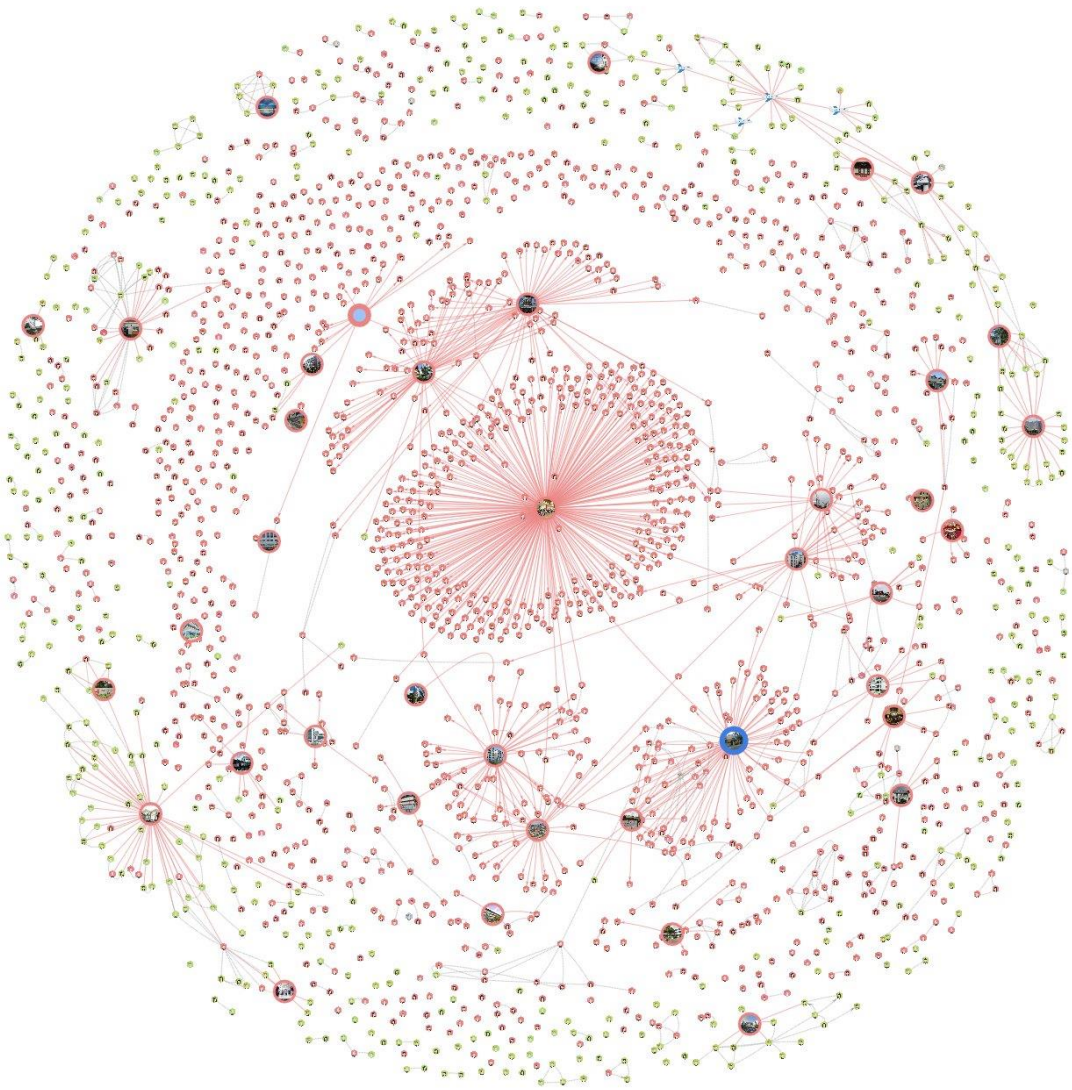
The failure at the core of the SEIR-model is fundamentally due to the concept of the basic reproduction number R0 or the effective reproduction number Rt, describing how many other persons an index person will infect. Through a series of complicated calculations, these numbers quantify the risk level of the disease spreading in a community. The lower the Rt is below the number 1, the lower is the risk, and vice versa [43]. For covid-19 the general R0 and Rt appear to be a combination of very many cases having with very low or no infectivity, very few cases causing very high rates of infections (super-spreaders). This so-called overdispersion, called k, seems to be particularly pronounced in the case of covid-19, as was recently proposed by Endo et al. [44], and has been elaborated on by a commentary in *Science Magazine* [45] as well as discussed and modelled in a recent and widely noticed paper by Althouse et al. on the importance of super-spreading in the covid-19 epidemic [46]. High overdispersion was already observed in the SARS and MERS outbreaks, so should not have been a surprise.

When super-spreading dominates the transmission dynamics as seems to be the case with covid-19, then general R0 and Rt of 10 or 3 or 1.5 or whatever the number might be, says almost nothing useful about the real infection risk a community faces. In the abstract we can imagine a community that is currently experiencing an Rt of far below 1, but still be exposed to a high risk of a super-spreader person or a super-spreader event which could trigger hundreds or thousands of infections within one day. At the other end of extremes, we can imagine a community that is currently experiencing a high Rt of 3 or 4 or even 10, caused by a recent super-spreading event (or import), but where the epidemic will quickly fade out due to the low degree of infectivity of covid-19 (as mentioned in section 1.2), as long as no more super-

spreading is taking place. In both cases the infection risk in the community is wrongly expressed by their current Rt. Instead they should be expressed by the risk of exposure to super-spreading. On this type of dynamic however, the Rt concept and the SEIR models are silent, even if they are enhanced with pareto distributions or negative binomial distributions.

A call not just for better models, but fundamentally different models has been issued by several research institutions [47] [48]. One such different approach are agent-based models which have been tried out to predict the progression of the covid-19 epidemic – however with discouraging results. For instance, a model from ETH Zurich proved to be wide off the mark [49], while recently a Finnish group suggested a REINA model that still needs to prove itself [50]. Karl Friston of University College London claims to have applied generative models successfully [51].

Figure 17: The case cluster map of Singapore as of 10 April



Source: againstcovid19.com/singapore/cases

5.2 Critical mass theory as an alternative

The inadequacy of SEIR models has been familiar to epidemiologists since the 1960s. For instance, Derek de Solla Price noted in 1965, that some events in the progression of an epidemic follow Pareto-style distributions (also called Power Law, Fat-Tail distributions, or commonly the 80-20 rule that 80% of the effect comes from 20% of the causes) [52]. To some degree, expanding the old SIR model from 1927 to become the SEIR model was a response to trying to incorporate power law dynamics in the models. More recently, Bettencourt and Ribeiro tried to adapt the SEIR model to account better for the dynamics of disease imports into a community, which are however only one of the sources of power law dynamics [53].

More fundamentally, applying the mathematics of exponential growth and power law to social and biological processes generates threshold dynamics, which can suddenly tip a person or a community from having a latent disease that is about to fade out, to an explosion of cases. How that is the case is well described in an article by Kevin Systrom [54].

This is not the place to invent a better modelling approach – but to direct attention to this threshold dynamic of the covid-19 epidemic, as is illustrated by the above case studies, and more of them described in Supplement V. It seems that the SARS-CoV-2 virus will in most cases fade out in a community after a couple of weeks and not export the infection to other communities. However, if a threshold has been surpassed, the virus is capable of transmitting slowly through a community for a long time, before suddenly and seemingly stochastically exploding into a surge of cases. These threshold dynamics suggest feedback loops of reinforcement mechanisms, both on the individual and community level, which urgently need to be investigated and better understood. For instance, if particular types of textiles, or particular utilization patterns of textiles provide such reinforcement mechanisms that lead to super-spreading, as could be concluded from the hypothesis that the early transmission dynamics in Europe was driven by textile events, then stopping this might be one possibility to prevent super-spreading. There is also the danger that wearing face masks can be a reinforcement mechanism. Unless it is investigated and understood, we cannot know. It is conspicuous that the first four super-spreader events of the proposed undetected European outbreak are textile-related.

Threshold dynamics would be well described by critical mass theory. The concept was developed in nuclear physics and has been successfully applied to sociology to describe sociological phenomena. Pioneers were Thomas Schelling or Mark Granovetter, the latter in his 1978 publication called "*Threshold Models of Collective Behavior*" [55]. Since the progression of an epidemic in a community is as much a social process as a biological process, it would make sense to consider using critical mass tools from sociology, to model and predict the progression of covid-19.

Every model is ultimately a simplification of reality, so that the workings of this reality can be understood in its separate pieces. The SEIR model is too far away from the actual dynamics of how the covid-19 epidemic progresses, to be able to provide useful insights. Unless the modelling of this disease becomes more adequate, we cannot hope to conquer it.

6. Conclusion

A detailed look at the German experience with the covid-19 epidemic, by stratifying the richly available data at the level of 16 states and 401 counties and cities, shows that the two nationally coordinated public policy bundles of mandatory social distancing (MSD) were not effective. The only bundle which had a strong and uniform effect across all 16 states, was not an MSD public policy bundle, but a voluntary and emergent reaction of business and private citizens taking place in the first two weeks of March, before the MSD measures came into force on 18 March. The other social distancing bundle which was highly effective to reduce the covid-19 epidemic came about because of the natural end of the carnival and winter vacation season on 01 March, but by definition it was only effective in those places where these two activities were prevalent.

After 09 March, public policy prohibited all large-scale events with more than 1000 persons, which was in all likelihood effective to prevent more super-spreading events such as festivals, fairs and concerts, and therefore could be called an effective public policy. Case study evidence from Bavaria seems to support this, but is confounded with the continuation of the Alpine winter activities. We have no evidence of German states where large scale events were allowed to continue, versus states where they were banned, so a direct observation of the scale of the effect is not possible.

In sum, at least within the German context, the two public policy bundles of shut-downs and contact-bans did not reduce the apparent transmitted reproduction number (Rta), also did not prevent the Rta from rising on the first summer-like weekend, and finally had no influence on the reduction during the Easter weekend. The data provides no measurable effectiveness. All reductions in Rta came about because of a voluntary response of society before those public policies were instituted, or because of the natural calendar event which put an end to two super-spreading activities of carnival and winter vacationing.

Finding answers to the question for why social distancing public policy was not effective in Germany, may require a fundamental rethinking of the epidemiological parameters of covid-19. One part of the answer may be that it is not useful to consider an R0 or even an Rt for this disease on a general level. Under normal social conditions, this Rt seems to be significantly below 1 and thus the disease does not sustain itself in a community. It is only in the combination of super-spreading persons and/or super-spreading events, when suddenly the infection system tips into explosive mode and creates a surge of infections. Allowing the combinations to repeat themselves – as in a vibrant bar and festival environment such as alpine après-ski – generates hundreds of thousands of infections in a short time-frame, which then literally infects an entire continent in lightning speed.

Therefore, efforts of public policy should be directed at stopping super-spreaders from engaging in super-spreading activities. This means either to stop such activities, or such spreaders, or both. If the currently arriving instruments of digitally supported contact tracing can identify super-spreaders fast enough, then the epidemic problem is solved, because then the virus cannot sustain itself anymore in communities and will fade out. Then even super-spreading activities would be safe, as long as they are not attended by super-spreaders, as the Cologne case study shows. If these contact tracing instruments are not yet effective enough, then further tools should be developed and tried out.

Resorting to the blunt public policy tool of enforcing blanket mandatory social distancing would be non-effective, at least for Germany, as the natural experiment of the 16 German states shows. Prohibiting the population from contacting each other and closing down public life, does not create a noticeable impact in the dynamics of the progression of the epidemic – and certainly not one that is worth the vast economic, social, cultural and political costs to society. Voluntary responses can achieve the same effect at less costs – but equally important to note is, that neither mandatory nor voluntary responses are sufficient to eradicate the disease.

An equally important is this: even now several months into the progression of the covid-19 epidemic, not enough is being done to gather, provide and analyze primary data, in order to better understand the transmission dynamics of the virus. For instance, there exists a major and inexcusable near-absence of virus mutation sequencing activity in Germany and Italy, so that the progression of the epidemic can be better followed and understood. Also, the near-time collection and surveillance of public health data to provide early warnings of epidemics in Europe is insufficient. Much evidence points towards SARS-CoV-2 spreading around German Bavaria and Austrian Tyrol in the thousands as early as December 2019. Even if it was not covid-19, something was causing undue numbers of deaths among the 20 million residents of Bavaria and Austria, and yet this fact was not noticeable until May 2020 in the numbers of the federal statistics agencies, and even then it has not yet been acknowledged to have occurred.

Much has been said and written about a seemingly belated public health policy response in the Chinese city of Wuhan that allowed the virus to slip out into the world before it could be stopped in the region. Yet there is not even direct evidence that China was the source of the epidemic. The failure of the authorities in Bavaria and Tyrol appears worse. Without being noticed by the authorities well into March 2020, it appears that the virus first slipped into the European textile and fashion industry, from there to the Alpine vacation festivals, and from there to every corner of the world – all of this in parallel to the Wuhan outbreak in China between December 2019 and February 2020. Even as of May 2020, not enough epidemiological investigations are arranged, and not enough testing is being conducted to monitor and understand the progression of the epidemic. Not enough of this data is made publicly available in a readily downloadable format so that different disciplines of researchers can work with the data and contribute their understanding. This insufficiency of providing primary data creation and collection, and the insufficiency to make it publicly available, hinders progress in solving the mysteries of the SARS-CoV-2 pandemic attack.

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